SAPIENZA
UNIVERSITÀ DI ROMA

Sapienza University of Rome

Doctoral School in Social Sciences and Economics
Curriculum: Public Policy Analysis and Evaluation

Thesis For The Degree Of Doctor Of Philosophy

Expenditure Heterogeneity, Income Shocks, and Redistributive Policies: Theory and Evidence from Italian Data

Thesis Advisor
Prof. Fabio Di Dio

PhD Candidate
Fausto Libero Barberis

Academic Year 2025-2026 (XXXVIII cycle)

Contents

List of Tables **iv**

List of Figures **vi**

Executive Summary **vii**

1 Literature Review on Consumption Elasticity **1**
1.1 Introduction . . . 2
1.2 Engel Curves . . . 3
1.2.1 The origin of Engel Curves . . . 3
1.2.2 Classical theories of consumption . . . 4
1.2.3 Recent literature on Engel Curves . . . 6
1.3 Income Effects on Consumption . . . 9
1.3.1 Link between micro-macro estimates . . . 14
1.4 Demand Curves and Price Elasticity . . . 15
1.4.1 Short history of the demand curves . . . 15
1.4.2 Food . . . 17
1.4.3 Energy . . . 18
1.5 Conclusion . . . 20

2 Expenditure, Income Variability and Heterogeneity: Evidence from Italian Household Data **23**
2.1 Introduction . . . 24
2.2 Related Literature . . . 28
2.3 The Data . . . 30
2.4 Descriptive Statistics . . . 31
2.5 Empirical Framework . . . 33
2.5.1 The Model . . . 33
2.5.2 The Quantile Regression . . . 35
2.6 Quantifying EIE Heterogeneity . . . 37
2.6.1 EIE Heterogeneity: The Role of Socio-Economic Variables and Demographic Factors . . . 37
2.6.2 The EIE across Expenditure Categories: Services, Durables and Non-Durables . . . 42
2.7 The EIE across time and the Covid Crisis . . . 47
2.8 Heterogeneity in Income Shocks . . . 50
2.9 Fiscal Policy Scenarios . . . 52
2.10 Robustness Analysis . . . 56
2.10.1 Household-level Analysis and Unconditional Quantile Regression . . . 56

2.10.2 Model Extensions . . . 57
2.10.3 Alternative sample selections and expenditure definition . . . 59
2.11 Conclusions . . . 60

3 The Multidimensional Welfare Effects of Italy's Minimum Income (RdC) 65
3.1 Introduction . . . 66
3.2 Main relevant related literature . . . 68
3.3 The Minimum Income Scheme in Italy: the implementation of the Citizenship Income . . . 72
3.4 Data . . . 74
3.5 Methodology . . . 78
3.5.1 Matching Difference-in-Differences . . . 78
3.5.2 Parallel trend assumption and matching balance . . . 79
3.5.3 Difference-in-discontinuity . . . 80
3.6 Results . . . 81
3.6.1 Effects on Well-being . . . 82
3.6.2 Effects on Labour market . . . 85
3.6.3 Heterogeneity analysis . . . 87
3.7 Conclusive Remarks and Policy Implications . . . 89

A Literature review resume 93

B1 Comparison of OLS and QR estimations 103

B2 Further model specifications 111

B3 Robustness checks 117

B4 Diagnostic tests 127

B5 Details on the dataset AD-HBS 131

B6 Model-based experiment details 137

C1 Difference-in-differences 139

C2 Difference-in-discontinuity 145

Bibliography 148

List of Tables

2.1 Descriptive statistics, averages from 2018 to 2022. 31
2.2 Summary of household average Income and Consumption (2018-2022). . . . 32
2.3 Total equivalent disposable income and ratio 80/20. 33
2.4 Decile regression Results: aggregate expenditure (2022) 39
2.5 Lines of individual expenditure and aggregated groups (2022) 43
2.6 Decile regression results: Services in 2022 44
2.7 Decile regression results: Non-durables in 2022 45
2.8 Decile regression results: Durables in 2022 46
2.9 Quintile Estimates (2018–2022) 48
2.10 Estimated shock parameters by period 51
2.11 Effect of Fiscal Policy Experiment (Transfers to Households) 54
2.12 Household equivalenced consumption and income (OECD-modified scale) . . 57

3.1 Eligibility Criteria of Reddito di Cittadinanza (RdC). 74
3.2 Distribution of individuals by year and treatment status. 76
3.3 Distribution of socio-demographic characteristics by treatment status. . . . 77
3.4 Regression results on poverty and consumption. 83
3.5 Regression results on labour market outcomes. 86
3.6 Heterogeneous Effects by Household Type 88

A.1 Resume table of the empirical papers analysed in Chapter I 93

B1.1 OLS yearly regression (2018-2022) 104
B1.2 Quintile Regression in 2022 105
B1.3 Quintile Regression in 2021 106
B1.4 Quintile Regression in 2020 107
B1.5 Quintile Regression in 2019 108
B1.6 Quintile Regression in 2018 109

B2.1 Regression Results for North 111
B2.2 Regression Results for Centre 112
B2.3 Regression Results for South and Islands 113
B2.4 Regression Results for Urban environment 114
B2.5 Regression Results for Rural environment 115
B2.6 Regression results for Services (2018-2022). 116
B2.7 Regression results for Nondurables (2018-2022). 116
B2.8 Regression results for Durables (2018-2022). 116

B3.1 Decile regression results: inclusion of liquid and illiquid wealth (ISEE) 118
B3.2 Decile regression results: inclusion of liquid wealth and home-ownership . . . 119
B3.3 Unconditional Quantile Regression results 120

B3.4 Decile regression results: inclusion of quadratic term. 121
B3.5 Quintile Results excluding income from retired people. 122
B3.6 Quintile Results excluding people under 18. 123
B3.7 Quintile Results excluding income from self-employed workers. 124
B3.8 Quintile Regression excluding imputed rents from consumption. 125

B4.1 White test, Cameron & Trivedi's IM-Test 127
B4.2 Machado-Santos Silva test for heteroskedasticity. 127
B4.3 Quantile regression Wald test to assess interdecile difference. 128
B4.4 Quantile regression Wald test to assess interquintile difference. 128
B4.5 Kurtosis statistics for each regression. 128
B4.6 Shapiro–Wilk Test for Normality of Residuals 129

B5.1 Descriptive statistics in 2022. 132
B5.2 Descriptive statistics in 2021. 133
B5.3 Descriptive statistics in 2020. 134
B5.4 Descriptive statistics in 2019. 135
B5.5 Descriptive statistics in 2018. 136

C1.1 Regression with fake treatment delivered in 2018. 143

C2.1 Diff-in-disc regressions with fixed ISEE threshold. 147

List of Figures

2.1 The Effects of Redistributive Transfer Programmes 55

B1.1 Conditional quantile regression 103
B1.2 Unconditional Q.R. 103
B1.3 EIE estimation over time 103

C1.1 Parallel trends for all the outcome variables. 140
C1.2 The outcome density before/after matching Treated - Controls. 141
C1.3 The reduction in selection bias of variables after matching. 142
C1.4 Event studies of consumption and poverty, year by year. 142

C2.1 McCrary manipulation testing plots. 145
C2.2 Discontinuity plots for each dependent variable. 146

Executive Summary

This study investigates household consumption in relation to economic resources, with a primary focus on elasticity. Elasticity is the responsiveness of consumption to changes in variables such as income or price. The thesis is structured into three chapters: a literature review on consumption elasticity, followed by two chapters of empirical analyses. The second chapter explores the elasticity of consumption with respect to income in Italy, while the third chapter evaluates the Italian guaranteed minimum income scheme, referred to as the *Citizenship Income*. The overarching theme is the examination of consumption patterns and consumer vulnerability, with the objective of formulating structured policy recommendations for Italy.

The first chapter examines the historical development of consumption theory and reviews recent literature on the empirical estimation of consumption elasticity. The analysis centres on two primary topics: Engel Curves and demand functions, specifically price elasticity. Engel Curves address the income elasticity of consumption, originating from studies of food expenditure as a necessary good in relation to disposable income during the XIX century. This concept demonstrates a consistent pattern in the reallocation of household budgets across income levels. The chapter offers a narrative overview and a literature guide, connecting classical theoretical frameworks with current empirical findings. Particular attention is given to food and energy, which represent essential goods and main expenditure categories for typical households. These goods display inelastic demand and a declining budget share as income rises. Empirical studies indicate that low-income households exhibit higher expenditure-income elasticity (EIE), or a greater marginal propensity to consume (MPC) in the *Keynesian* fashion, compared to wealthier households. Consequently, lower-income groups allocate a larger proportion of their income to consumption, highlighting the significant influence of financial constraints. This relevant evidence from literature connects to Chapter II, which explores this topic in the Italian context, and enhances the policy implic-

ation that redistributive policies or targeted transfers can boost aggregate consumption, as discussed in Chapter III.

The second chapter presents estimates of the Expenditure-Income Elasticity for Italy, using a unique dataset comprising annual repeated cross-sections from 2018 to 2022. This dataset merges administrative data (AD) on income with the Household Budget Survey (AD-HBS) on consumption, as well as various socio-demographic characteristics. A semi-structural log-log model of consumption, based on the reduced-form of Engel Curves, is estimated using quantile regression methods at different points of the income distribution. The empirical analysis yields four principal findings.

First, the results provide strong evidence of substantial heterogeneity among agents in spending behaviour. The elasticity decreases consistently across quantiles and remains persistent over time. Specifically, it declines from 0.203 in the first decile to 0.146 in the tenth decile, representing a 5.7 percentage point difference, or approximately a 40% variation, in 2022. This finding aligns with the theoretical predictions of Heterogeneous Agent New Keynesian (HANK) models, which emphasise the importance of liquidity constraints and inequality.

Second, the analysis demonstrates the significant influence of socioeconomic and demographic variables on expenditure estimates. Labour status, family size, and geographic location are identified as crucial determinants of expenditure behaviour.

Third, the estimates vary considerably across consumption categories. Durable goods exhibit higher coefficients, especially among lower-income households, reflecting their discretionary nature. In contrast, non-durable goods and services display lower and more stable elasticities, as these categories typically represent essential consumption. These patterns underscore the importance of disaggregated analyses for capturing the nuances of household spending behaviour.

Fourth, the analysis for 2020 and 2022 indicates that external economic shocks, including the pandemic outbreak and the inflation spike, significantly affect elasticities across all income groups. These events resulted in a sharp decline in expenditure, particularly among low- and middle-income households, due to increased economic and political uncertainty and restricted consumption opportunities.

Finally, a model-based experiment replicates the estimates and a static fiscal-transfer exercise compares the heterogeneous specification with the representative-agent benchmark.

A uniform transfer generates weak aggregate consumption responses compared to targeting the lower tail of the income distribution, where elasticities are higher. These findings are consistent with previous research and underscore the importance of accounting for household heterogeneity. Recognising this heterogeneity is essential for assessing the distributional effects of income changes on consumption and the effectiveness of fiscal interventions. This concern paves the way for the last Chapter, which suitably examines the effects of a subsidy to lower income levels.

The final chapter applies a standard policy evaluation framework to Italy's minimum income scheme, *Reddito di Cittadinanza*. This programme was designed as a last-resort safety net to protect vulnerable groups, reduce household poverty, and act as an automatic stabiliser by supporting consumption and reducing deprivation. These transfers alleviate liquidity constraints, enable more stable expenditure patterns, and improve access to essential goods and services. As a result, they generate broader social benefits in health, education, and social cohesion, especially during periods of economic downturn.

This quantitative study uses the same dataset as the previous chapter and examines the entire period of the measure, including two years before its introduction. Reddito di Cittadinanza (RdC), introduced in 2019, was a means-tested programme that combined income support with labour activation objectives and remained in place until 2023. The research offers a comprehensive assessment of multidimensional welfare impacts. Six metrics are employed: income-based relative poverty, consumption-based absolute poverty, household aggregate expenditure, and unemployment, employment, and inactivity shares. The identification strategy relies on a difference-in-differences approach with propensity score matching, supplemented by a difference-in-discontinuity design around eligibility thresholds. This approach isolates causal effects and addresses selection bias and compositional concerns.

The analysis shows that RdC reduced relative poverty by 5 percentage points and absolute poverty by 4 points among beneficiaries compared to similar non-recipients. These results confirm the programme's effectiveness in improving living standards and reducing material deprivation among households at the lower end of the income-consumption distribution. The scheme functioned as a critical safety net for the most vulnerable during economic shocks, consistent with existing literature on minimum income schemes in Italy.

The programme also increased aggregate household consumption by approximately 4 percent, demonstrating a significant role in sustaining demand, including during the Covid-

19 period. This result aligns with economic theory and international evidence, which indicate that transfers to liquidity-constrained households typically lead to high marginal propensities to consume. The observed increase in consumption underscores direct welfare gains that support adequate living standards and help smooth consumption during income shocks.

However, the analysis also identifies a modest increase in unemployment of approximately 6 percentage points among beneficiaries, along with a corresponding decrease in employment share and a mild increase in inactivity. Several mechanisms may explain this outcome, including strictly limited integration with formal employment and the absence of a robust activation platform. In some cases, benefits may interact with informal employment, particularly in contexts with high levels of undeclared labour. These findings highlight the complex trade-offs that policymakers face in designing anti-poverty programmes, particularly regarding activation measures and long-term fiscal sustainability. Although the scheme is no longer in place, its removal may threaten social cohesion and exacerbate inequality within the country.

In conclusion, the thesis provides a comprehensive analysis of the determinants of consumption behaviour and the concept of elasticity. It further investigates the impact of income distribution on variability among households, highlighting the importance of these factors in evaluating fiscal and redistributive policies. Additionally, it offers a detailed examination of the recent Italian context.

Chapter 1

Literature Review on Consumption Elasticity

Abstract

This study presents a review of contributions investigating how household consumption responds to changes in income and/or prices (consumption elasticity). The study focuses on two primary areas: Engel curves (income elasticity of consumption) and demand functions (price elasticity of demand). After outlining the evolution of consumption theory, the analysis points to more recent contributions. It also highlights recent advancements in addressing the issue of heterogeneity and aggregation. Empirical evidence shows that low-income households have a systematically higher propensity to consume than wealthier households, suggesting that redistributive policies or targeted transfers can significantly amplify aggregate consumption. Overall, this review provides a guide to the literature on consumption elasticity, bridging classical models with contemporary empirical insights to inform both theoretical modeling and empirical policy analysis. In Appendix A, a resume table of all empirical papers analysed is provided.

Keywords: Elasticity, Theory of consumption, Price, Demand functions, MPC.

1.1 Introduction

This article presents a literature review on the broad relationship of income, consumption, and prices. It covers two broad strands of literature: the Engel Curves, which define the relationship between income levels and consumption, and the analysis of the demand as a function of prices. The concept of elasticity is thus crucial for analysing this relationship. In the first case, a key role is played by the elasticity of consumption with respect to income, namely the sensitivity to income variations. In the second case, the coefficient of interest is the price-elasticity, namely the variation of expenditures as a result of a change in price levels.

The aim of this review is thus to provide a narrative introduction to the topic, mixing some history of the theoretical foundations with the most recent advancements at the research frontier. The topics have a long tradition in Economics, but, in the past century, they were mainly theoretical, while nowadays many studies are focused on the empirical estimation of these relationships. The existing literature has evolved and developed throughout time, with multiple models of consumption: several models of consumption are introduced, sometimes entailing contradictions between theory and data, with different policy implications.

The chapter starts from an overview of the well-known Engel Curves in Section 1.2, going from the original definition of the author in Section 1.2.1, through their evolution over time, including a summary of the recent works on the topic in Section 1.2.3. In Section 1.2.2, the theoretical ground of consumption is addressed, analysing the main scholars of the past, primarily Keynes. Those consumption models are still the foundations of current research, but the availability of data dramatically changed the way of working. Indeed, there are different methods nowadays to study the expenditure-income elasticity (Marginal Propensity to Consume (MPC)), as elucidated in Section 1.3. The theoretical models of consumption then try to replicate the results of the empirical analyses, as seen in Section 1.3.1.

The second part of the chapter is thus devoted to the analysis of demand function, in Section 1.4. A short history of the demand curves is provided, starting from Marshall and Hicks, in Section 1.4.1. A specific discussion on the price elasticity is dedicated to the main lines of an average budget share: food consumption in Section 1.4.2, and energy in Section 1.4.3. Finally, Section 1.5 summarises and concludes. Appendix A provides a resume table (A.1) of the papers and some demand function equations.

1.2 Engel Curves

An Engel curve describes how household expenditures on a given good or service vary with the disposable income, keeping the prices fixed. The goods or services are normally aggregated into total spending of specific categories (e.g. food, clothing, transport). Under fixed prices, linear Engel curves can be viewed as Marshallian demand functions, which describe how real expenditure varies with household income. For normal goods, the Engel curve has a positive slope, since the quantity demanded increases as income increases. The slope is steeper for necessary goods than for luxury ones, due to the relative change in consumption share. For inferior goods, the slope is negative since the household consumes less quantity as income increases.

1.2.1 The origin of Engel Curves

Ernst E. Engel (1857, 1895) was the first to systematically study the relationship between income and the composition of household expenditure. Using an empirical–inductive approach with budget data from roughly 200 Belgian households and, without sophisticated mathematics, he documented a seminal regularity: as household income rises, the budget share devoted to food tends (probabilistically) to decrease. Engel's Law is not a rigid linear postulate but an empirical regularity admitting exceptions and calling for flexible models.

Then, a centenary reassessment was made by Houthakker (1957), which generalised Engel's Law and confirmed it across countries. Expenditure elasticities by category (and household size effects) display similar patterns internationally. The core principle is widely observed: the food shares are declining with rising income, food is a necessity with elasticity below one. Housing often shows near-unit elasticity, clothing and transport are frequently above one, since they can be viewed as luxury goods.

In that period, Working (1943) and Leser (1963) proposed the classic *Working–Leser specification* in which each category's budget share is a linear function of the logarithm of total expenditure (and prices). Elasticities follow straightforwardly by differentiating the share equation, although the model does not directly estimate income elasticity per se.

In Gorman (1961) and Gorman and Deaton (1981), the author introduced the *Gorman polar forms*, which is a functional form for indirect utility functions. He derived an explicit expression for preferences that yields linear Engel curves, with expenditure function linear in utility. The Gorman polar form is a necessary and sufficient condition to represent society

as a single consumer, with aggregate utility function and aggregate demand curve.

Another way of expressing the Engel curves is in terms of budget share (Deaton, 1985): they describe how the proportion of household income spent on a good varies with income. The concept is related to the composition of the consumption basket and relative nature of goods and services. For instance, the subsistence consumption of normal goods declines in relative terms, while the importance of luxury expenditures rise. See the Appendix A for the related formulas.

1.2.2 Classical theories of consumption

The relationship between income and consumption has been widely studied in the literature, especially during the XX century. The three main pillars are represented by the work of Keynes, Modigliani and Friedman.

Keynes (1936), in *The General Theory of Employment, Interest and Money*, developed the macroeconomic relationship with the current available income as the main driver of consumption (the so-called hypothesis of absolute income). Indeed, he is considered the inventor of the *Marginal Propensity to Consume* (MPC). This last concept determines by what extent consumption changes in response to income variation. It is a crucial link between micro-evidence and macro-models and it must be comprised in a range between 0 and 1. The *Average Propensity to Consume* (APC) is, instead, complementary and represents the average income spent. Normally, it declines as the income level rises and is higher than MPC, due to the presence of the so-called autonomous consumption.

Subsequently, Modigliani and Brumberg (1954) formulated the *life-cycle hypothesis*. The mentioned theory assumes that the agents are purely rational who maximise their inter-temporal consumption, predicting their income over the entire cycle of life. Thanks to the knowledge of the income prospect, they adjust their consumption over time, internalising all the possible income shocks.

Very similar to those concepts, Friedman (1957) developed the *Permanent Income hypothesis* in *A Theory of the Consumption Function*. He divided income into a transitory and a permanent components. Consumption is then driven by the latter one, because is not function of the current income. The Keynesian theory is then completely reversed.

A variant of the previous models is represented by *Income, Saving and the Theory of Consumer Behavior* (Duesenberry, 1949), where he explored the interdependence of prefer-

ences (hypothesis of relative income). This means that consumption is also driven by the relative position of the agents, introducing somehow the concept of positional goods. This approach recalls the *Emulation Theory* proposed by Thorstein B. Veblen (1899), since the preferences are also shaped by the dominant classes. The positional goods have the function of seeking the *status quo* in a relative comparison of the social hierarchy, as further explained by Hirsch (1976) and Frank (1985).

Theil (1965) and Barten (1969) proposed the *Rotterdam Model*, a simple, theoretically grounded instruments for analysing temporal changes in consumption. It has a differential form system linking (infinitesimal or finite) changes in demanded quantities to changes in prices and total expenditure. It is linear in first differences and well-suited to time-series data, but it has main local interpretation and is not highly flexible.

Then, Christensen et al. (1975) introduced the *Transcendental Logarithmic* model, based on a second-order Taylor expansion of the log indirect utility function in prices and income. With a high substitution flexibility and interpretable parametric structure, however, it had limited flexibility for Engel curves and potential violations of concavity and instability.

Another fundamental step in consumption analysis was made by Nobel Prize laureate Angus Deaton. In Deaton and Muellbauer (1980), they proposed the *Almost Ideal Demand System* (AIDS). The AIDS belongs to the family of flexible functional forms, with large flexibility and adherence to extensive empirical evidence, consistent with budget constraints, simple to estimate, and with clear economic interpretation. At a micro level, it is a standard tool for estimating elasticities from household data. The AIDS system satisfies adding-up automatically, with simple parameter restrictions, homogeneity and symmetry, and it aggregates over consumers without requiring parallel Engel curves. It implies that, as income rises, the budget share of goods with elasticity below one declines, and their income-elasticity falls.

A widely used specification is the *Linear Approximate AIDS* (LA/AIDS), since the non-linear price in parameters can be computationally demanding. It is a practical shortcut when full estimation is too costly: it shares the same assumptions as AIDS (adding-up, homogeneity, symmetry), with a simpler estimation process and approximately preserved theoretical properties. Engel curves for expenditure share are linear in the logarithm of total expenditure.

In Deaton (1988), he refined the analysis on how to estimate real prices and demand elasticities, when only unit values - and not market prices - are available in household surveys.

It allows to estimate Engel curvature using consumption microdata only, and exploiting spatial variation. This separates price from quality, corrects measurement error and quality choice, and permits estimation of demand elasticities.

The evolution of the previous model, proposed by Banks et al. (1997), is the *Quadratic Almost Ideal Demand System* (QUAIDS). It extends the previous AIDS by allowing greater flexibility of Engel curves, with the same assumptions and improved empirical fit. It considers a non-parametric analysis of consumer expenditure patterns, which suggest that Engel curves require quadratic terms in the logarithm of expenditure. QUAIDS model lets budget shares depend quadratically on the log of income to exhibit the required curvature: for luxury items, spending initially rises with income and later declines in budget-share terms, consistent with luxuries becoming relative necessities as income grows. For necessary goods, Engel curves have limited curvature and are close to linear in log-income.

More recently, Blundell et al. (2003) affirmed that standard neoclassical consumer theory with stable rational preferences can account for much aggregate household behaviour when the data are flexibly analysed. Then, Blundell and Stoker (2005) explored how individual heterogeneity shapes aggregate relationships. The neglect of income distribution, credit constraints, and demographics could bring to aggregate bias of macroeconomic parameters. Thus, the representative-agent shortcuts can be misleading.

These models are not mutually exclusive and have evolved over time. Empirically, different models often yield qualitatively similar elasticities, particularly when theoretical constraints are imposed and the data are informative. A thorough analysis might estimate multiple specifications in order to check the robustness of the consumption functions. In Section A, there is a list of the main demand function equations mentioned in this paragraph.

1.2.3 Recent literature on Engel Curves

In recent times, Engel Curves are still on the research frontier. Many different strands of literature have been developed around this concept. This is a non-structured literature review, with some of the most relevant and original contributions to the topic.

Chai and Moneta (2010) gave a historical retrospective, since they replicated the original study of Engel and highlighted the innovative design. For instance, the original tabulations produced with a moving-window regressogram resemble modern non-parametric methods.

Chakrabarty and Hildenbrand (2016) resumed the original study and proposed to frame the Engel Curve as a negative stochastic dependence between income and the food share, so a property of the entire joint distribution, giving credit to the first non-parametric statistical analysis of budget-data.

In Moneta and Chai (2014), they examined the evolution of Engel curves, focusing on the saturation of consumption beyond a certain income level. The curves are flattening over income distribution, and that is true for most of goods and services. Even if the saturation is dynamic and context-dependent, the importance of accounting for preferences shifts and income distribution is crucial for long-term consumer demand models.

Aguiar and Bils (2015) adopted an Engel demand approach to assess whether consumption inequality has tracked income inequality. They used double differencing across categories with different income-product elasticities and non-homothetic preferences, and they concluded that U.S. consumption inequality has risen almost as much as income inequality since 1980. The gap in the share of voluptuary consumption widened over the period considered, confirming the previous results of Attanasio and Pistaferri (2014), but contrasting the ones of Krueger and Perri (2006).

Chai et al. (2015) analysed the related concept of diversification of consumption and variety along the income brackets. Using UK microdata, the authors tailor the consumer shapes of households. Low-income families are homogeneous and oriented toward subsistence consumption, while high-income level expenditures are strongly heterogeneous, both in terms of aggregate level and of variety. The conclusion is that entropy positively increases with income. In the same branch, but in a completely different setting, Li (2021) confirmed that households with higher expenses tend to consume a wider set of varieties, and that diversification in India, along the years considered from 1983 to 2009, yielded sizeable welfare gains. Furthermore, Clements and Si (2018) found that higher income is associated with greater dietary diversity and quality across countries. The elasticity of diversity with respect to income per capita is $\sim$0.3 on average. The analysis is carried out on 31 categories in 150 countries, and relative prices often favour the access of richer countries to higher quality foods, with distributional implications.

Chai (2018) tried to link household consumption patterns with the theories of structural change. The effect of Engel's law could explain economic transformation, like the case of agricultural sector. Its share declines with higher per-capita income, while the weight of services rises. The demand for agricultural products grows less than income and, thus, re-

sources are oriented towards new sectors (e.g., industrialisation, financialisation). Moreover, non-homothetic preferences generate growing demand for quality and variety. This study recalls the pioneering works of Pasinetti (1981) and Foellmi and Zweimüller (2008). Relatedly, Comin et al. (2021) estimated a demand system with non-homothetic CES preferences in a multi-sector model of structural change. They found that income effects explain most within-country sectoral reallocation, and that services display higher income elasticities, agriculture lower, manufacturing in between.

Clements (2019) revisited four laws of consumption and established a *strong law* and *reciprocal law* of Engel. The former implies that there is a continuous log-linear relationship between food share and income (around 10 points loss each income doubling); the latter states that the food share tends to 100% when income is approximately null, while it tends to zero when in income is almost infinite. He documented cross-country regularities around those consumption laws.

The paper of Clements et al. (2022) explored the heterogeneity and non-linearity of household consumption. They estimated a linear expenditure system on Australian microdata, dividing the sample by income quintiles. The simulation with heterogeneous households produces more fit and credible Engel Curves than the homogeneous LES model (as formulated by Stone (1954) and Geary (1950)). The income brackets can capture most of the nonlinearity and the diversity of consumption patterns.

De Vreyer et al. (2020) highlighted a less focused topic, such as the intra-household inequality. They separated the household- and individual-level consumption using Senegalese data. The Engel curves (à la Working-Leser) are not distorted - the two levels are overlapping - if all the family members experience a proportional rise in income, and if the individual preferences are separable.

The study of Sancho (2024) tries to combine LES model with a constant elasticity substitution (CES) shifted functions in computable general equilibrium (CGE) models. The aim is to generalise the utility function and to overcome restrictive constraints – like unitary elasticity of substitution or homotheticity, implicit in functions of Cobb and Douglas (1928) type – and to allow for different elasticities of substitution, more adherent to empirical evidence.

Atkin et al. (2024) used quasi-separable Gorman preferences to allow exact income-specific price indices and non-parametric estimation of *relative* Engel curves across the income distribution, when well-measured prices are not always available. In two waves in rural India, 1987 and 2000, they found a differential inflation by percentile; a welfare measurement

should account for heterogeneous price exposure.

In Sologon et al. (2025), the authors explored the spike in energy prices during 2021-22 in Europe. The inflation was remarkable for food goods and utilities. Starting with HBS data, they analysed the specific inflation for income groups, and they found that it acted as a regressive tax with a disproportionate burden on vulnerable households (except for Finland). The liquidity constraint of this latter group amplified the effects of the general rise in prices.

Kang and Vasserman (2025) provided a new approach to assess the robustness of welfare measurement, when specific functional forms are assumed. They formulates indices to quantify how much the true demand must deviate - in terms of slope changes and curvature - from the specification to overturn a welfare result. High gradients imply robust conclusions, while low values indicate fragility. The framework complements the literature on curve flexibility.

1.3 Income Effects on Consumption

Recalling Section 1.2.2 about the theory of consumption, this part is dedicated to go through the empirical estimation of the effect of income on consumption. A key concept in this field is the *Keynesian* Marginal Propensity to Consume, the elasticity of consumption with respect to a change in income. Jappelli and Pistaferri (2010), in *The Consumption Response to Income Changes*, made an extensive review of the literature on how consumption reacts to income changes. They found three main strands in the literature about the estimation of the MPC.

The first one is the quasi-experimental evidence, a method which is based on the exploitation of an exogenous shock without the estimation of an income process. The main advantage of this approach is that the identification strategy is clear and straightforward. On the other side, it has a limited use and can identify only specific shocks, and some of them are not totally exogenous, so with difficult application.

Firstly, Bodkin (1959) studied the behaviour of veterans after receiving the World War II dividends, and he found a very high MPC (0.72), especially on non-durables, which is against the permanent income hypothesis. Another example concerns the use of weather data and climate shocks, as done by Wolpin (1982) and Paxson (1993). The former studied precipitations in India and estimated a permanent income elasticity between 0.91 and 1.02, while the latter found a higher marginal propensity to save out of weather shocks in Thailand.

Gruber (1997) analysed the occurrence of unemployment status: with anticipation, there is no consumption smoothing; without, the smoothing is large. Similarly, Browning and Crossley (2001) confirmed the liquidity constraint hypothesis.

Another way of doing a quasi-experimental analysis is to use health data, like Gertler and Gruber (2002) who use minor illnesses as transitory shocks and major ones as permanent. There are also many ongoing attempts to exploit the COVID-19 pandemic as quasi-natural experiment, especially in China, but not strictly related to consumption literature.

The second wide approach to MPC estimation is represented by self-reporting from survey questions. The innovation is the easiness of the measure, since it is auto-declared directly by households. Nevertheless, the drawback is that perception could be biased and not aligned with real data.

A pioneering work was done by Shapiro and Slemrod (1995), in which they evaluate the fiscal stimulus of Bush Sr presidency. They found that liquidity-constrained individuals were more likely to spend the extra revenue. The authors deepened the analysis in Shapiro and Slemrod (2003), finding also a substantial portion of US households paying off their debts after the transfer. Households would not see an extra-revenue (temporary positive shock) as an additional resource to their lifetime income, as, on the contrary, predicted by the *Life Cycle Theory of Consumption* and the *Permanent income hypothesis*. They conducted a similar third experiment in Shapiro and Slemrod (2009) on the 2008 tax rebates.

Analogously, Johnson et al. (2006) analysed the 2001 tax rebates. The average household spent between 20 and 40% on non-durable goods during the three-month period in which the rebate was received. The expenditure responses were largest for low-liquid wealth and low-income household, consistent with liquidity constraints. Parker et al. (2013) empirically studied the fiscal stimulus pack of 2008 in USA, when the households received an extra-revenue *una tantum*. On average, they spent between 50% and 90% of the transfer, among which 12%-30% in nondurables and a general rise of durables, like vehicles. The effect was stronger for low-income, older or home-owner households.

From those studies, Jappelli and Pistaferri (2014) took inspiration for their seminal article. They examine the fluctuation of consumption based on wealth distribution. Data is from the 2010 *Survey on Household Income and Wealth* (SHIW) of the Bank of Italy, in which respondents self-declare their income level and wealth endowment, along with a marginal propensity to consume out of hypothetical extra-revenue of the amount of a monthly salary (positive shock). They found evidence of a strong decline in MPC over the income

distribution, with a total average of 0.48, along with a flat consumer profile over working life until retirement and a predictable positive correlation with unemployment status. Hence, aggregate consumption is influenced by the elasticity distribution. In Jappelli and Pistaferri (2020), they replicated a similar analysis based on the *Survey on Household Income and Wealth* (SHIW) of 2016. Results confirmed MPC declines with resources availability and liquid assets as its key drivers.

More recently, the aim of Albacete et al. (2025) is to evaluate the effects of heterogeneity in MPC on the effectiveness in EU fiscal policy, recalling the seminal work of Jappelli and Pistaferri (2014). This last work was focused on Italy, while the authors extended it to the Eurozone. Instead of SHIW data, they used HFSC (Household Finance and Consumption Survey) from ECB. The results are analogous in terms of wide heterogeneity across agents and countries: the total average is 0.46, going from 0.33 in the Netherlands to 0.57 in Lithuania. Nonetheless, the patterns within nations are systematic, with *cash-on-hand* households displaying higher MPCs. In the end, accounting for the heterogeneity better fits reality and increases the effectiveness of policies.

Moreover, Bunn et al. (2018) e Christelis et al. (2019), instead, explored the asymmetry between positive and negative shocks (stronger responses in the latter case regarding the former), while Nakajima (2020) found a significant heterogeneity in the income-consumption elasticity according to the household indebtedness in Japan.

Immordino et al. (2022) exploit the effect of fear of COVID-19 contagion and income risk on consumption. They found evidence of a drop in consumption, and a relative increase in savings during the pandemics due to the fear of contagion in Italy. The income uncertainty also played a central role.

The third and last way to estimate MPC is a semi-structural model. It requires specific assumptions about the income process in order to identify the households response to income shocks. Normally, scholars pose covariance restrictions for the identification of parameters of the joint distribution of income and consumption. The availability of panel data, or quasi-panel, helped the dissemination of this kind of works. The econometrician should know the stochastic process which generates individual income expectations.

A first example of this genre was the study of Hall and Mishkin (1982), who worked with PSID data on income and food consumption and used quadratic preferences. They found that consumption responds more to permanent movement of income, and that life cycle (permanent income) behaviour accounts for most of household consumption, while the

response of consumption to innovations in transitory income is 29%.

Attanasio and Weber (1995) used labor supply variables from 1980 to 1990 as determinants of the marginal utility of consumption to account for non separable preferences and to avoid spurious evidence of excess sensitivity. Parker (1999) used security payroll cap as an anticipate income increase and decrease afterwards, in a sample of high-income taxpayers. They discovered that 1$ anticipated rise in income increased nondurable consumption by about 20 cents, unlikely to be due to liquidity constraints. Souleles (1999) exploited the anticipated income increase induced by the receipt of tax refunds. 10% of the refunds were spent on non-durables and 65% on total consumption suggesting that most of the refund was spent on durable goods.

Blundell et al. (2008) created a panel data on a comprehensive consumption measure for the PSID using an imputation procedure based on food demand estimates from the CEX. They found that consumption is nearly insensitive to transitory shocks (around 5%, but higher among poor households), while they suggested that households are able to insure at least part of the permanent shocks. Their findings suggest that the widening gap between consumption and income inequality is due to the change in the durability of income shocks. Specifically, a growth in the variance of permanent shocks was replaced by a continued growth in the variance of transitory income shocks by the end of last century. The relative increase in the variability of more insurable shocks explained the disjuncture between income and consumption inequality.

Stephens (2008) used predictable increases in discretionary income following the final payment of a vehicle loan. A 10% increase in discretionary income leads to a 2% to 3% increase in nondurable consumption. Additional analysis suggests that these findings may be explained by the presence of borrowing constraints.

Misra and Surico (2014), using a quantile regression approach, confirmed those results. After analysing the 2001 and 2008 tax rebates, it was discovered that low-income households and tenants showed a high tendency to spend, especially those with considerable mortgage debt. The heterogeneity of consumption is concentrated in just a few nondurable and durable categories.

Bernheim et al. (2001) investigated the explanations for the variation in savings for retirement, in relation to wealth, consumption levels and growth rate. Life-cycle models attribute the variability to differences in time preference, risk aversion, exposure to uncertainty and relative preferences for work and leisure. The authors used PSID-CEX panel data from 1978

to 1990 at different points of the distribution (quartile). They found evidence of a substantial consumption drop at retirement (24% for the first income quartile, 15% for the second quartile and 9% of the third and fourth quartiles). The data are more consistent with the hyperbolic discounting (Laibson, 1997), or *rule-of-thumb* and *mental accounting* theories, rather than with classic models.

Lewis et al. (2024) estimated the unconditional distribution of the MPC using clustering regression on the 2008 economic stimulus payments. They recovered the full distribution and found that households spent between 4 and 133% of the rebate within a quarter. Household observable characteristics explain only 8% of MPC variation, the other part highlights the role of latent heterogeneity.

J. D. Fisher et al. (2020) focused on the synergy among income, consumption, and wealth inequality in defining the life-cycle budget constraint. These joint distributions are important in evaluating macroeconomic impacts of changes in income because the response may differ across the distribution. The heterogeneity in the response affects significantly the effectiveness of government fiscal policy. The authors used PSID data from 1999 to 2013 to define the marginal propensity to consume across the wealth distribution. As expected, MPC is lower at higher wealth quintiles, while low wealth households cannot smooth consumption. The implication is that increasing wealth inequality likely reduces aggregate consumption, and, as a consequence, it might limit economic growth.

Mian et al. (2013) analysed, from a different perspective, the effect of negative wealth shocks on consumption. They used data on the fall of retail prices during the Great Recession in U.S., exploiting the geographical variation in 2006-09. The estimated consumption-wealth elasticity is about 0.6-0.8, with a strong wealth effect, similar to a permanent income effect. The impact was stronger for low-income or indebted households. Kaplan et al. (2020) confirmed those results using similar data and different approaches.

Another work on the wealth effect is the one of Campbell and Cocco (2007), where they studied the trend of British retail prices. A rise in the house value stimulates consumption in older households, while the effect for young renting people is negligible. This results highlights a direct price effect and the heterogeneity of the wealth effect (permanent income).

1.3.1 Link between micro-macro estimates

Krusell and Smith (1998) established a seminal result showing that a complete-market (representative-agent) economy can approximate the aggregate behaviour of an incomplete-market (heterogeneous-agent) economy, albeit at the cost of greater computational and data requirements in the latter case. On top of that foundation, a growing body of research has focused on improving the implementation and calibration of macroeconomic models. Contemporary macroeconomists are primarily concerned with the amplification and transmission of both aggregate and idiosyncratic shocks, for which the choice of model specification is pivotal. Although different models may exhibit similar aggregate responses to shocks, they often diverge in their underlying transmission mechanisms (see Kaplan and Violante (2018)). Within this line of inquiry, Kaplan et al. (2014) investigated wealthy hand-to-mouth households possessing only illiquid assets, while Kaplan and Violante (2022) provided a systematic review of the proper calibration of macro models to align them with micro-level data.

Using data from the Survey of Household Income and Wealth (SHIW), Krueger et al. (2024) examined household budget adjustments in response to labour income shocks, extending an earlier analysis (Krueger et al., 2016). Their findings indicate that households primarily absorb income shocks through variations in net wealth rather than consumption (self-insurance), and that fixed-asset ownership significantly affects this adjustment process. The study further argues that there is not a uniform marginal propensity to consume (MPC) across households, but rather it depends on the characteristics of those experiencing the shock. Consequently, policy evaluations must account for the distribution of shocks across households with different levels of wealth and debt, a conclusion also reached by Auclert et al. (2023).

Consistent with this, Carroll et al. (2017) demonstrated that the estimated average MPC (approximately 0.20) depends critically on the distribution of shock recipients and is not a structural constant of the economy. Their study highlights that wealth distribution is a key determinant of policy effectiveness and suggests that monetary authorities should account for consumer heterogeneity in policy design (see also Bilbiie (2008)).

Fagereng et al. (2021) conducted an innovative natural experiment on Norwegian lottery-winners, providing further micro-level evidence. They found that MPCs are close to unity ($\simeq$1) for small prizes and liquidity-constrained households, but decline sharply ($\leq$0.5) with greater wealth, age, and prize size. These results have important implications for the target-

ing of fiscal transfers and for understanding the transmission of monetary and fiscal policy.

Finally, Kaplan and Violante (2022) provided a systematic review of heterogeneous-agent macroeconomic models capable of generating empirically realistic MPCs, ranging from 0.2 to 0.6, and close to 1 for *hand-to-mouth*, including the *wealthy*. Empirical estimates suggest MPCs of approximately 0.25 (0.15) following transitory income shocks of $1,000 ($500), respectively. To conclude, their analysis reinforces the idea that modern macroeconomics of consumption must explicitly incorporate the substantial heterogeneity of household financial conditions.

1.4 Demand Curves and Price Elasticity

This part is devoted to resume some noteworthy articles on the price elasticity on consumption. After an introductory paragraph, which deals with a short history of the demand curves and the relative price elasticities, a specific focus is oriented toward food and energy components. Those components are the most relevant in the household budget share for the majority of people, and for that reason are here reported. Nonetheless, there are other fields where scholars have studied elasticities, like tobacco, transport, health, not reported here since they are beyond the scope of this article.

1.4.1 Short history of the demand curves

Alfred Marshall (1890), in his *Principle of Economics*, is considered the inventor of the neoclassical demand curve. This concept was explained through a Cartesian diagramme, with the unit price on the horizontal axis and the demanded quantity on the vertical one. Thus, the curve indicates the potential quantity required for each level of price, *ceteris paribus*. The framework is a partial equilibrium model, keeping all the other variables fixed. This aspect is crucial, and it differentiates the X-diagramme of the Marshallian cross with respect to computationally difficult general equilibrium models à la Walras (1874).

Marshall cleared the individual demand, affected by income and preferences, distinguished from the market demand, which the sum of individual curves. Generally, the Marshallian demand curve is decreasing, because of the principle of the diminishing marginal utility. The demand law states that higher prices imply a lower demand, and viceversa. A well-know - rather rare - exception is represented by the *Giffen goods*, a paradox which

implies a positive correlation between demand and price.

Moreover, he introduced the concept of demand elasticity. This measure expresses the sensitivity of the quantity in relation to price variations. From his analysis, the elasticity is normally negative, as a corollary of the demand law. The demand-price elasticity can assume various shapes: elastic if the demand for goods varies more than proportionally to price change (higher than one), otherwise rigid or inelastic (if lower than one), and unitary (if equal to) as a peculiar case.

Before Marshall, already Edgeworth (1881) and I. Fisher (1892) made the ground for an ordinal approach to preferences. That means that utility of consumption must be at least ordinal in order to design the indifference curves, a crucial concept introduced by Pareto (1906) which refers to the relative preferences of different combinations of consumption. Each curve defines a possible relationship of the consumption of two goods, holding constant utility. This concept is linked to the fundamental works of Hicks (1939, 1956). He finalised the previous theories with the introduction of the *compensated demand*, named after him as Hicksian demand. This concept exhibits the optimal demanded quantity as a function of price changes, holding the utility level fixed. Starting from this, he introduced the notion of elasticity of substitution between two distinct goods as a function of relative prices. He showed that the Marshallian demand is related to the compensated one by the demand elasticity to income. In case of normal goods it is positive, while for inferior goods is negative, and it explains also the paradox of Giffen goods. He also defined the equality of the marginal rate of substitution to the price share as optimal condition of consumption, where the indifference curve is tangent to the budget constraint. This approach allowed to define the substitute and complementary goods, according to the relative cross-price elasticities of demand. The former have negative elasticity with respect to the alternative good, while the latter the opposite sign.

The demand curve is then founded on the rationality of consumers, which find all the possible combinations along the demand curve to maximise their utilities, given an individual budget constraint. The negative slope reflects the trade-off between marginal utilities and relative prices along the optimal frontier. All the substantial work of Hicks benefited from the previous less-known studies of Slutsky (1915). He formulated the decomposition to disentangle the price effects on the demanded quantity. The total effect could be decomposed in two components, the substitution effect and the income effect. Isolating the first, it is possible to compensate the price variation in order to keep the utility level constant.

His equation allows to reposition along the original indifference curve, and distinguish the Marshallian demand function from the compensated one.

Subsequently, well-known scholars like Samuelson (1948) refined the analysis, introducing the revealed preferences, starting from individual demand instead of assuming a specific utility form. Given some conditions, like completeness, transitivity and non-satiability of preferences, it is possible to derive the individual curve which satisfies standard properties, like negative demand-price elasticity and non-negative substitution effect, without knowing the cardinal utility.

Afterwards, beyond the scope of this discussion, many other scholars explored the possible violations of rational preferences, which alter the standard theory. One of the most famous example is the non-rationality analysis in the behavioural *prospect theory* of Kahneman and Tversky (1979), establishing an asymmetric response to positive or negative shocks because of the different psychological perception.

1.4.2 Food

The consumption of food products, other than one of the main lines of expenditure, has also been widely addressed in the literature. As mentioned in Section 1.2.1, Engel originally studied the relationship between food consumption and income. It has always been, notably for low-income households, the main expenditure in the household budget.

Andreyeva et al. (2010) conducted a seminal literature review of 160 U.S. studies, from 1938 to 2007, on own-price elasticities of food demand, mainly for dietary policy purposes. Food demand is generally inelastic, indeed the mean absolute elasticities span from ∼0.27 to ∼0.81. When the category is disaggregated, the estimates are very diversified: the more price-responsive items include sugar-sweetened beverages (∼0.79), fruit juices (0.76), food away from home (0.81), meats (0.68–0.75), fruit (0.70), and cereals (0.60); the less responsive ones include eggs (0.27), sugars and sweets (0.34), cheese (0.44), fats and oils (0.48). Those estimates indicate that large price changes are typically required to induce sizeable consumption responses in an inelastic demand sector.

Cornelsen et al. (2015) and Green et al. (2013) made global systematic reviews with attention to cross-price elasticities of food consumption. The effects of rising income are double, since quantity and quality both change. The study considered 78 articles on aggregate demand from 38 countries - with different development levels. Demand is generally

more price-responsive in low-income countries, and cross-price effects vary with development level and dietary diversity. In high-income settings, richer substitution or complementarity patterns emerge. For instance, a 10% increase in cereal/bread prices reduces cereal consumption by ∼4.3%, and slightly raises purchases of fruit and vegetables (+0.5%), meat (+0.45%), fish (+0.75%), dairy (+1%) and even sweets (+0.57%). In addition, Cornelsen et al. (2016) showed that methods matter: the research design, the model specification, the unit values, and the outcome definitions systematically affect elasticity estimates. The *one-size-fits-all* could be misleading in this field. Very recently, Jeon et al. (2025) addressed the issue of possible distortions between meta-analyses on food consumption and economic theory. They tried to estimate the fundamental demand elasticities using QUAIDS, and they used a matrix of elasticity to consider jointly the own-price and the cross-price elasticities to avoid biased estimates.

A well-known article by Jensen and Miller (2008) explored the nature of the Giffen goods, through an experimental evidence of staple foods in subsistence conditions in China. Those goods are with a positive demand-price elasticity, rather rare in reality. Those subsidies for staples reduced their consumption, under the conditions of tight budget constraint and inferior-good dynamics.

1.4.3 Energy

The other main component of an average household budget regards the utilities and energy consumption. Here there is a non exhaustive list of the most recent contributions in the field.

Alberini et al. (2011) studied the elasticities of different energy sources in U.S., considering the climate and regional heterogeneity. The own price elasticity of electricity is around -0.8, while the one of the gas demand is -0.6. They found strong household response to energy prices, both in the short and long term, and the warmer regions have more elastic responses.

Hastings and Shapiro (2013) analysed how households react to oil price shocks. When the price goes up, consumers tend to lower the quality with cheaper gasoline, due to not only to income effect but also to mental accounting. The money for fuels is though not perfectly fungible with total income. The authors explain that with behavioural theory, since consumers are not perfectly rational.

Labandeira et al. (2012) faced the difficulty in estimating the price elasticity of energy with incomplete data on households and firms, and they use panel data with fixed-effects to control for unobserved heterogeneity. The energy demand is on average inelastic in the short-run, and it becomes more rigid for rich households and big firms. This fact yields the risk of regressivity in case of energy shocks. Labandeira et al. (2017) did a meta-analysis of gasoline demand, and they report evidence of short-run price elasticity around -0.21, and long-run around -0.61, but with substantial heterogeneity.

Coglianese et al. (2017) studied the gasoline demand elasticity in presence of taxes or time leads and lags. The estimated elasticities are reasonably lower, around -0.37, because of the possibility of stockpiling or delayed expenditure. Huntington et al. (2019) summarised gasoline elasticities for major industrialising economies, regularly finding very inelastic short-run gasoline demand.

Belaïd et al. (2020) adopted a quantile regression to estimate the heterogeneous direct rebound effects in French residential electricity consumption. They found evidence of price elasticity around 0.38-0.71 and efficiency elasticity 0.72-0.86, with substantial heterogeneity among quantiles. The lower bound is at the first decile and the upper bound at the last decile, indicating that gasoline is more inelastic for low-income households.

Hahn and Metcalfe (2021) evaluated a large-scale energy subsidy in California (CARE), which discounts natural gas tariffs for low-income households. They estimated a price elasticity of around -0.35. Trotta et al. (2022), analysing the data from the residential heating demand in Denmark, highlighted that price elasticities are heterogenous according to several dimensions. For instance, single households display higher coefficients, large consumers are more elastic, and poor families are more reactive, even if there is not unique evidence in literature.

Liddle and Huntington (2020, 2021) analysed differences in terms of development stage, with a dataset of 78 countries for more than 50 years. For high-income countries, the energy elasticity is around -0.22 in the long run, while for non-OECD the elasticity is close to zero (∼–0,08) and non-statistically significant. This means that developing countries exhibited a lower price elasticity, along with a higher income elasticity, and the authors suggested irreducible subsistence consumption, subsidies and regulated prices as possible explanations. Gao et al. (2021), using the same dataset but with a different nonlinear econometric approach, confirmed an energy price elasticity between -0.1 and -0.3.

Peersman and Wauters (2024) applied a direct survey to Belgian households to estimate

the energy elasticity and the MPC after an energy shock. They found asymmetric responses, stronger for price hikes (-0.36) than to decreases (-0.07), confirming the misperception of agents. Moreover, elasticity tends to be lower for larger shocks (-0.29 instead of -0.43), and responsiveness is higher among low-income households. Finally, the MPC is 0.59 for the rise and 0.40 for the fall in prices, recalling the asymmetric response for different shocks.

Priesmann and Praktiknjo (2025) examined the elasticity of domestic energy consumption, and they also considered income heterogeneity. Non-homogeneous households exhibit different sensitivity to price. Low-income families have a short-run energy elasticity of -0.27 and a long-run of -0.22; high-income families, respectively, of -0.44 and -0.64. They also did the analysis for natural gas and fuels.

Miller and Alberini (2016) analysed, instead, the sensitivity of the price elasticity to methodology and data used in U.S. Since many papers studied the domestic energy demand, but estimates vary considerably, the authors explained this difference primarily because of aggregation issues, unobserved heterogeneity, and missing variables. Aggregation generally smooths the variability of prices and softens behavioural preferences, while part of the elasticity is due to the specific household characteristics. For these reasons, it is necessary to control for permanently divergent aspects (e.g., habits, attitudes, housing status, capital stocks) to avoid bias or overestimation. On the contrary, endogeneity issues and specific time trends do not appear to play a significant role.

Finally, Bobasu et al. (2025) proposed a HANK model for the euro area, with exogenous shock of the inflation spike in 2022. The energy-price shocks have regressive impacts and interact with monetary policy, since the rise in interest rate could amplify the effect.

1.5 Conclusion

This literature review focuses on two main strands about consumption elasticity, such as the Engel curves (income elasticity) and the demand functions (price elasticity). It provides a guide to the literature on the topic and also highlights recent advancements in addressing the issue of heterogeneity and aggregation. Table A.1 delivers a detailed list of the examined papers.

The Engel curves, despite the fact that were introduced more than 150 years ago, are still a highly relevant topic in Economics. They are crucial for the estimation of the elasticity between income levels and consumption expenditure. In particular, they explain the shift in

the consumption basket from the low-income brackets to the highest ones. In this pattern, food and energy are the main components of an average budget share. These budget lines yield inelastic behaviour and diminishing share over the income distribution, since they are necessary goods or services.

In parallel, the theory of consumption has developed over time. Starting from Keynes, with the concept of the Marginal Propensity to Consume (MPC) out of the current income, to the Life-Cycle theory and the Permanent Income hypothesis, where households are able to self-insure against temporary income shocks and their consumption levels are only affected by permanent shocks. Nowadays, it is widely accepted in the literature that household financial conditions, either disposable real income or accumulated wealth, strongly affect consumption patterns. So why does studying elasticity matter?

Empirical analyses systematically show that low-income households have higher propensity to consume than the better-off. This resume highlights that accounting for the heterogeneity of consumption elasticities across the distribution of economic endowments matters for assessing the impact of fiscal policies. This fact creates a link to structural models and suggests that targeted redistributive policies may benefit aggregate consumption.

Chapter 2

Expenditure, Income Variability and Heterogeneity: Evidence from Italian Household Data

Abstract

The paper provides estimates of the elasticity of expenditure relative to income for Italy, using a quasi-panel dataset from the Italian Household Budget Survey (AD-HBS) between 2018 and 2022. Specifically, we estimate the Expenditure-Income Elasticity (EIE) using quantile regression methods at different points of the income distribution and with different characteristics of the population (working and marital status, type of income - labour, pensions and transfers -, demographic characteristics, geographical location etc.) and type of goods (durables, non-durables and services). We observe significant heterogeneity in the EIE distribution, which is strictly decreasing across quantiles and persistent across time. We observe extraordinary reductions in the waves of 2020, due to the pandemic outbreak, and in 2022, with the inflation spike and increased uncertainty related to the Russia–Ukraine war. The analysis highlights the importance of accounting for household heterogeneity when assessing the distributional effects of income changes. We discuss the relevance of the results for evaluating spending responses to fiscal interventions and redistributive scenarios.

Keywords: Consumption Elasticity, Income Heterogeneity, Redistribution, Quantile Regression.

JEL classification: D12, E21, H23, C21.

2.1 Introduction

Recent studies have emphasised the relevance of heterogeneity in expenditure decisions as a result of income shocks and how this aspect plays a crucial role in understanding the transmission mechanisms of fiscal and monetary policy[1]. In fact, whereas the classical models of consumption often rely on a representative-agent framework, a growing body of research has highlighted the key role of the distribution of expenditure choices across income, demographics, and expenditure categories (see, e.g., Andreolli and Surico (2026), Albacete et al. (2024) and Jappelli and Pistaferri (2014)).

This paper seeks to empirically investigate the elasticity of expenditure relative to income in Italy, namely how potential income variations might affect expenditure decisions. Specifically, the study analyses the distribution of Expenditure-Income Elasticity (henceforth, EIE) including key socioeconomic and demographic dimensions that may vary across the income distribution, somehow highlighting its heterogeneity in spending behaviour.

While our analysis shares some conceptual similarities with the Marginal Propensity to Consume (MPC), it departs from standard MPC analysis in significant ways. In the first place, unlike studies that rely on longitudinal panel data to estimate dynamic consumption adjustments[2], on quasi-experiments, or direct measurement (survey questions), the present analysis employs a semi-structural log-log model of consumption framed around reduced-form of *Engel curves* - basically, relationships that describe how household expenditures vary with income -, then estimated using a quasi-panel dataset. Through quantile-based regressions, we provide estimates of the elasticity of consumption with respect to income across different household strata (see Deaton (1985) for estimation with repeated cross-sections).[3]

Importantly, given the repeated cross-sectional data structure to infer consumption behaviour, we abstract from intertemporal considerations such as whether income changes are permanent or transitory. Indeed, the analysis focuses on the sensitivity of the expenditure responses of households to exogenous income changes, independent of the nature of the income shock. In this respect, the methodology does not require to take a stand on specific

[1] A number of important macroeconomic implications of heterogeneous responses of expenditure decisions as a result of income shocks have been recently investigated in the Heterogeneous Agent New Keynesian (HANK) literature. See, among others, Kaplan et al. (2018) and Auclert (2019).

[2] Many of these approaches rely on dynamic models that explicitly account for intertemporal considerations, such as the persistence of income changes or their expected nature. See, for example, Fagereng et al. (2021), Carroll et al. (2017), Krueger et al. (2016).

[3] Following Deaton (1985), a large literature has documented that the relationship between total outlays and consumption is generally non-linear and heterogeneous across the cross-sections. See J. Engel and Kneip (1996) for the methodological advancements in the estimation of Engel curves.

income shocks in order to identify them, that is often challenging in this type of analysis (see, for example, Jappelli and Pistaferri (2020)).

Nonetheless, by abstracting from shock identification strategies, our methodology emphasises the sensitivity of household expenditures to income variations across different income strata, demographic groups and types of goods. By using Engel curves to estimate expenditure decisions in a quasi-panel setting, this paper contributes to the methodological literature linking income variability and expenditure decisions in Italy. In this respect, the closest predecessors of the analysis are Dao et al. (2024), Guglielminetti and Rondinelli (2024) and Caceres (2019), among others, who seek to understand the relevant drivers of household consumption using static Engel curves. See Section 2.2 for more details.

Furthermore, while traditional MPC studies often rely on average effects estimated through Ordinary Least Squares (OLS - see, among others, J. D. Fisher et al. (2020)), our quantile regression framework allows us to capture heterogeneity in consumption behaviour across the entire income distribution. This enables a more granular analysis of how income changes impact different population groups and types of expenditures, offering insights that extend beyond the scope of standard MPC estimation.

Concerning the data, the analysis uses the quasi-panel AD-HBS dataset, which merges the Italian Household Budget Survey with administrative records. Covering the period from 2018 to 2022, the AD-HBS dataset provides annual representative samples of the Italian population with detailed information on consumption, income, and socioeconomic characteristics. The dataset's quasi-panel structure consists of repeated cross-sectional surveys, which ensure time consistency by reproducing the distribution of key population characteristics over time. It includes a wide range of variables, such as age, marital status, family size, income quintiles, region of residence, and employment status. Additionally, the data categorises consumption expenditures into 13 main groups, such as food and beverages, housing and utilities, health, and transportation, based on the COICOP classification (UN, 2018). Administrative data enrich the dataset by providing detailed information on income sources (labour, pensions, subsidies) and individual fiscal conditions (e.g., tax liabilities and benefits).

Beyond this, the AD–HBS linkage is particularly well suited to our empirical strategy. First, the administrative component delivers disposable income measured from tax records and decomposed into earnings, pensions, and transfers at the individual level, thereby reducing classical measurement error in self–reported incomes and allowing us to condition on

income sources in a transparent manner. In this sense, the granularity of income composition and fiscal detail allows us to trace heterogeneous expenditure responses across the distribution and by income source in a way that survey-only or bank-account data typically cannot match. Second, the survey component provides nationally representative, large-sample repeated cross-sections with a rich set of covariates (labour-market status, demographic composition, geographic indicators) and proxies for wealth (ISEE, home-ownership), which we explicitly use in the specifications to investigate heterogeneity across different characteristics of the sample. This is why the dataset properly supports the distributional analyses by income source and demographic groups, advantages that are hard to attain with survey-only data or with administrative aggregates used in previous contributions (see, for instance, Jappelli and Pistaferri (2014)). Third, the annual coverage over 2018–2022 enables consistent comparisons of estimated elasticities across markedly different macro environments without the attrition and selection issues typical of panels. While the data are not longitudinal, the repeated cross-section design preserves the population distribution over time and, when coupled with administrative income and fiscal records, delivers precisely the details our quantile framework requires.

Furthermore, while this methodology allows us to capture the impact of disposable income changes on consumption for various population groups, at the same time it enables to quantify the extent to which the estimates of the impact from the homogeneous response model may be inaccurate. A common finding of the papers estimating MPCs, regardless of the approach, is indeed the strong evidence for MPC heterogeneity relative to their homogeneous model counterparts (see, for example, the findings of Jappelli and Pistaferri (2014)).

Concerning the estimation methodology, we allow the variation to spend out of potential income changes to vary across household groups, which are determined within the estimation method. In this sense, quantile regression offers a robust framework to uncover heterogeneity by modeling the conditional distribution of consumption expenditures at various points of the income distribution. Unlike ordinary least squares (OLS), which focuses on average effects, quantile regression captures variations in EIE across different quantiles, providing insights into how income changes impact expenditure behaviour for both lower- and higher-income households. Indeed, this analysis quantifies the extent to which the estimates of the impact from the homogeneous response estimates may be inaccurate relative to their heterogeneous model counterparts. This approach is thus particularly suitable given the substantial variability in income and consumption distributions observed in the AD-HBS

dataset. As documented in the literature (see, e.g., Misra and Surico (2014)), quantile regression effectively addresses issues of skewness, kurtosis, and heteroskedasticity that are common in cross-sectional data. Moreover, by estimating the elasticity at multiple points in the distribution, it allows for a better understanding of how household characteristics, such as income, demographic factors, and regional disparities, drive consumption responses.[4]

Our empirical analysis leads to four main findings. First, the results reveal significant heterogeneity in expenditure estimates across income quantiles and household characteristics. As a matter of fact, lower-income households exhibit substantially higher elasticities compared to their higher-income counterparts, consistent with the theoretical expectations of liquidity constraints and limited access to credit markets, without the possibility of insurance against the income risk. We observe that the EIE variation (2022 data, see Table 2.4) between the first (0.203) and the tenth decile (0.146) is approximately 5.7 percentage points (corresponding to 39%). This is consistent with the empirical analysis by Cho et al. (2024) showing that change in consumption behaviour is consistent with tighter borrowing constraints more than a shift in wealth distributions.

Second, we document that socioeconomic and demographic heterogeneity is a first-order driver of consumption behaviour: conditioning on labour-market status, household size, and geographic context substantially improves fit and systematically shifts the estimated income–expenditure elasticities, which should therefore be interpreted as conditional on observables rather than as unconditional responses.

Third, EIE estimates vary notably across different categories of consumption. Durable goods exhibit higher values, particularly among lower-income households, reflecting their lump-sum and discretionary nature. In contrast, non-durable goods and services show relatively lower but more stable elasticities, as these categories often represent essential consumption items. This difference emphasises the importance of disaggregated analyses to capture the differences in household spending patterns.

Fourth, the analysis carried out in 2020 and 2022 reveals that external economic shocks, such as the COVID-19 pandemic and the Russia-Ukraine war, significantly affect elasticities across all income groups. These events led to a sharp decline in expenditure decisions, particularly among low- and middle-income households, by virtue of the heightened economic

[4]The methodology is also consistent with the theoretical predictions of Heterogeneous Agent New Keynesian (HANK) models, which emphasise the critical role of liquidity constraints and income distribution in shaping macroeconomic outcomes. See, for example, Kaplan and Violante (2018) and Kaplan et al. (2018).

uncertainty and constrained consumption opportunities.

We also connect this empirical evidence to policy by using the quantile-based estimates to evaluate simple fiscal-transfer counterfactuals. We contrast a representative-agent benchmark — where a uniform transfer implies a single average EIE (namely, OLS estimates) — with our heterogeneous specification, in which the same transfer is filtered through the full distribution of EIEs. The key message which emerges is that uniform transfers (namely, OLS) deliver smaller aggregate consumption responses than policies that concentrate the same budget on high-EIE households (i.e., the lower tail of the income distribution), thereby magnifying the short-run effect of a given fiscal impulse. Moreover, a decomposition of the aggregate effect shows that half share of the welfare gains reflects distributional heterogeneity (differences across quantiles), and the remainder is attributable to observable characteristics (captured by the control covariates).

The paper is structured as follows. Section 2.2 frames the paper within the relevant literature linking income variation to household expenditure. Section 2.3 presents the AD-HBS dataset, while Section 2.4 reports some descriptive statistics of the dataset. Section 2.5 provides details about the regression model and the estimation methodology. Section 2.6 reports the results of the benchmark model for the year 2022. Section 2.7 explores the stability of the results over time. Section 2.8 explores the role of heterogeneity in income shocks over time by comparing the empirical distribution of the EIEs with the one resulting from a small dynamic heterogeneous agent model. Section 2.9 provides a series of policy experiments to illustrate how the quantile EIE estimates could be used to assess the aggregate spending response to redistributive fiscal measures. S Section 2.10 reports some robustness checks. Section 2.11 concludes.

2.2 Related Literature

The present analysis sits at the intersection of two main strands of literature linking income variation to household expenditure. One strand of this literature takes a similar approach to our contribution, allowing the elasticity of consumption with respect to income to vary across households with different features. In particular, the closest predecessors of our paper are those studying the EIEs accommodating household heterogeneity through the estimation of the elasticity across income (or wealth) and socio-economic characteristics. Relevant examples include Dao et al. (2024), Guglielminetti and Rondinelli (2024) and Caceres (2019).

In detail, Dao et al. (2024) estimate the EIEs during the post-pandemic recovery of U.S. private consumption, decomposing the drivers of spending across population groups and documenting distributional differences consistent with heterogeneity in liquidity constraints and balance-sheet positions. Their results emphasise that aggregate recoveries mask substantial cross-sectional variation in consumption responses — an insight that directly motivates our quantile approach to the Italian case. Guglielminetti and Rondinelli (2024) provide evidence on distributional differences in households' consumption adjustments to macro shocks for Italian households, reinforcing the view that responses depend on households' characteristics - a key principle of our quantile specification, while Caceres (2019) shows that financial and housing wealth are important correlates of consumption at the micro level, with effects that vary across the distribution, thereby linking wealth positions to differential spending sensitivities (EIEs), an aspect we proxy for through income composition and wealth indicators in our controls.

A second strand of literature focuses on estimating elasticity across income (and/or wealth) quantiles and/or types of goods. Misra and Surico (2014) study the 2001 and 2008 U.S. tax rebates and, using quantile methods, document sizeable heterogeneity in spending responses along the income distribution. They find that low–income households, renters, and highly indebted mortgagors display markedly higher propensities to spend out of transitory income, and that much of the adjustment is concentrated in a handful of (non-durable and durable) expenditure categories. Their key message is that distributional heterogeneity — not the average — drives the aggregate effect of stimulus. Consistent with Misra and Surico (2014), our estimates feature a declining EIE across quantiles, larger responses among liquidity-constrained groups (e.g., unemployed or fixed-term workers), and disproportionate adjustment in durables. Consistent results are in Arellano et al. (2024), Harold et al. (2017) and Parker (1999). Complementary to event-study designs, J. D. Fisher et al. (2020) infer MPCs from the joint cross-sectional distributions of income, consumption, and wealth, providing an aggregation strategy that is well suited to settings where long panels are unavailable. Their emphasis on the mapping between balance sheets and spending propensities speaks directly to our use of detailed administrative covariates (income sources, fiscal status) combined with household budget data: we likewise leverage rich cross-sections to recover heterogeneity - here via quantile regressions of expenditure on disposable income and controls - and to connect differences in EIE across the distribution to differences in resources and financing capacity.

2.3 The Data

The AD-HBS is an annual representative sample of the Italian resident population. It merges the survey data on consumption expenditures of the Household Budget Survey (HBS) provided by the *National Institute of Statistics* (ISTAT) with the administrative data (AD) from *National Social Security Institute* (INPS). It has a quasi-panel structure: each wave of HBS is a separate cross-section of sample with different individuals, but it keeps the same distribution across time and reproduces the key characteristics of the Italian population. The database covers five consecutive years from 2018 to 2022 and the time consistency is ensured by scaling up all the variables to yearly values.

A large set of socio-economic and demographic variables is available to individuals (age, familial status, gender, level of education, family size, presence of children, region of residence, degree of urbanisation, type of contract and work, income quintile) and the categorisation of consumption follows the division of ISTAT into 13 main groups of goods and services: food and beverages, alcohol and tobacco, clothing, utilities and housing, furniture, health, private and public transport, media and telecommunications, sport and culture, education, accommodation and restaurant, finance and insurance, and personal care.

On the other hand, the administrative data tracks individual information on labour earnings, pensions, and transfers (subsidies) allowing for differentiation of income sources as well as working status and employment contract. Specifically, total disposable household income has been aggregated into three main sources: pensions, subsidies and labour income. Each of them is then assigned to the respective working category (e.g. employed, unemployed, retired, etc.), and through this process the individual income is thus obtained.

Among the various types of transfers, there are child benefits and public family allowances (ANF), minimum income transfers like *Inclusion Income* (ReI) in 2018 and *Citizenship Income* (RdC) from 2019, and other unemployment allowances. These latter benefits are disaggregated according to the working category (*NASpI, DIS-COLL*, and agricultural). In addition, the redundancy fund (CIG) records the salary compensation due to work suspension. The pensions are grouped as retirement, survival, disability, and others. Concerning the labour income, tax liabilities (IRPEF) are applied individually with a tax rate relative to the corresponding taxable income, and thus disposable income is the difference between gross income and tax liabilities.

Furthermore, the *Equivalent Economic Situation Indicator* (ISEE), which assesses the

comprehensive financial situation of a family, is also available. For further details about the AD-HBS, please refer to Aprea et al. (2023) and Aprea et al. (2024), and see Appendix B5 for further clarifications.

2.4 Descriptive Statistics

Table 2.1 presents the relevant demographic variables of the sample in the AD-HBS dataset as mean values from 2018 to 2022.[5] All the values are to be interpreted as percentage shares, except for the first two lines in which we report the average age (46.7 years), and the average family size (2.26 individuals per household).[6]

Table 2.1: Descriptive statistics, averages from 2018 to 2022.

Variable	Mean	Median	St.Dev.
Age	46.72	49	23.174
Family size	2.26	3	1.292
Female	51.80%	1	0.500
Married	45.42%	0	0.498
North	44.52%	0	0.497
Centre	21.99%	0	0.414
South & Islands	33.49%	0	0.472
Metropolitan area	15.78%	0	0.364
Medium-size cities	29.44%	0	0.456
Small municipalities	54.78%	1	0.497
Age(<30)	25.81%	0	0.437
Age(30-50)	25.98%	0	0.438
Age(50-65)	24.14%	0	0.428
Age(>65)	24.07%	0	0.427
Family size (1)	14.25%	0	0.349
Family size (2)	28.40%	0	0.451
Family size (3)	23.66%	0	0.425
Family size (4)	24.24%	0	0.428
Family size (5+)	9.46%	0	0.292
Tenants (rent)	16.39%	0	0.370
Home-ownership	75.79%	1	0.428
Unemployment rate	6.79%	0	0.251

Notes: Descriptive statistics of the AD-HBS dataset. Values are population-weighted averages of the yearly samples and are to be intended as fraction (percentage) of the total.

[5] For more statistics about the AD-HBS dataset see Appendix B5.

[6] Both variable are also further detailed: family by numerosity (e.g. single 14.2%, couples 28.4%, large families 9.5%, etc.), and the share is calculated out of total number of individuals, not of total households; and age is almost equally divided by brackets (<30, 30-50, 51-65, >65) by construction.

Female individuals account for 51.8% of the population, while married people or registered partnerships are 45.4% of the total. Concerning the geographical location, 44.5% of the family lives in the North, 22% in the Centre, and 33.5% in the South and islands (Sicily and Sardinia). Relative to the residence, 15.8% lives in a metropolitan area, 29.4% in a medium-sized city (above 50.000 inhabitants) or in a periphery suburb of a big city, and the 54.8% in a small town or village (below 50.000 inhabitants). The large majority of households owns its dwelling (76.8%), while there is relevant minority of tenants (16.4%). Eventually, the aggregate unemployment rate is on average 6.8%, in line with the aggregate national statistics.

Table 2.2: Summary of household average Income and Consumption (2018-2022).

Variable	**2018**	**2019**	**2020**	**2021**	**2022**
Labour Income*	38,831.61	38,549.23	37,756.13	40,952.81	41,641.66
Retirement Pensions*	24,698.85	26,069.13	26,559.94	27,099.93	27,519.99
Unemployment Benefit*	3,053.74	5,430.15	4,032.35	2,999.88	3,210.42
Public Transfers* (Other)	1,598.28	2,602.93	2,425.37	2,537.26	1,239.39
Minimum Income (ReI, RdC)*	2,131.50	3,659.35	5,194.67	-	5,185.60
Total Consumption	34,540.42	35,102.75	32,398.22	33,840.41	35,295.74
Utilities & Housing	11,288.95	11,432.99	11,653.43	11,590.75	12,007.18
Food & Beverage	6,436.62	6,526.30	6,646.18	6,647.75	6,864.00

Notes: Summary of the economic indicators of the dataset, expressed in monetary terms. A unique average is not provided due to the different inflation rates and purchasing power throughout the years.
∗ Values are referred only to effective recipients or reporting agents.

Table 2.2 presents some economic statistics, mainly concerning income and consumption for every year of the sample. Data are at current prices and collected on an annual basis. The average family (disposable) labour income follows an upward trend over the time span considered, being around 39,000 euro per year in 2018 and 42,000 in 2022.[7] Retirement pensions are around 26,500 euro annual per household, while unemployment benefit accounts more than 3,000 euro per year. Other public transfers have been aggregated under the item *Public Transfers (Other)*.[8]

The minimum income scheme has gone through two stages: a less generous *Inclusion Income* (ReI) in 2018, and the well-known *Citizenship Income* (RdC) from April 2019 onwards, which provided more substantial support. The RdC-related transfers have shown a substan-

[7]For those who received a public subsidy or pension, the average values are referred only to effective recipients and not to the whole sample.

[8]The overall disposable income is defined as the sum of all the components of income sources, pensions, subsidies and various transfers.

tial leap in 2020 as a result of the stabilisation measures during the pandemic crisis. Data on annual consumption follows similar path, being total consumption around 35,000 euro yearly. The main two components are *Utilities & Housing* (energy, rent), ranging from 11,000 and 12,000 euro per year, and *Food & Beverage*, with almost 7,000 euro of expenditure.

Table 2.3: Total equivalent disposable income and ratio 80/20.

Quintile	2018	2019	2020	2021	2022
I	10,926.45	12,096.36	11,410.70	13,179.40	12,861.49
II	22,682.52	23,815.08	23,391.89	27,001.56	26,076.32
III	32,571.05	33,296.19	32,800.27	37,494.30	37,454.14
IV	45,611.01	45,930.78	45,346.22	48,793.95	51,717.20
V	75,014.00	75,858.61	76,748.78	70,934.46	89,641.29
Ratio (80/20)	6.87	6.27	6.73	5.38	6.97

Notes: Table shows the average values of the equivalent-income quintiles across time. The Ratio (80/20) is a standard measure of inequality, i.e. the ratio between the values of the fifth and the first quintile.

Table 2.3 reports the average total income per year and quintile, and the corresponding ratio 80/20 between the fifth and the first bracket. They are built starting from income distribution in the population, considering the total disposable income of households, divided by the family size and equivalenced by the OECD-modified scale (for the economies of scale).[9] The total equivalent disposable income is then ordered and split into the classical five quintiles. The table suggests that income of the top 20% is around six times the one of the bottom 20% all over the years considered.[10]

2.5 Empirical Framework

2.5.1 The Model

To investigate the heterogeneity of the Expenditure-Income Elasticity (EIE) among Italian households, we employ a linear model of consumption behaviour,[11] in the spirit of Deaton (1985), tailored for a quasi-panel structure. This approach is well-suited to the AD-HBS

[9]This scale, proposed in 1994, assigns a value of 1 to the household head, of 0.5 to each additional adult member, and of 0.3 to each child.

[10]Such a value is aligned with the results presented in the 2024 annual *Report on Equitable and Sustainable Wellbeing (BES) indicators*, AA.VV. (2024).

[11]This could be interpreted as a reduced-form Engel curve model. More recently, Blundell et al. (2003) and Blundell and Stoker (2005) explored consumer expenditure patterns and how individual heterogeneity shapes aggregate relationships, while Imbens (2004) implemented a fully non-parametric demand system.

dataset[12], which combines repeated cross-sectional data from the Household Budget Survey (HBS) with administrative records from the National Social Security Institute (INPS).[13] Specifically, the model accommodates household-level heterogeneity in consumption responses to changes in disposable income, while controlling for various socio-demographic characteristics, highlighting how demographic and regional factors influence the EIE and its distribution.

We thus adopt the first two specifications to estimate the EIE for different groups of individuals exploiting the joint information of household types and their relative position in the income distribution (quintile or decile distribution). The unit of observation is a single individual, within an identified household. Subsequently, individuals which share certain socio-economic and demographic characteristics, are then aggregated and analysed in a *stratum* level. It is worth noticing that we carry out the analysis at the individual level to better exploit all the characteristics provided by the dataset, including working status or age of individuals. Nonetheless, for sake of comparability, in Section 2.10.1 we employ also the household-unit level.

We also provide estimates for type of goods. Following Misra and Surico (2014), we classify goods into durables, non-durables, and services to capture distinct patterns in consumption responses. Durable goods, such as vehicles, often exhibit higher income elasticities but are less sensitive to short-term income fluctuations, whereas non-durables and services tend to reflect immediate changes in household budgets. This categorisation allows us to link our findings to broader economic theories of consumption smoothing and precautionary savings.

Specifically, we consider the following Engel curve:

$$e_{i,h,t}(j) = f_j(y_{i,t}, s_{h,t}) \tag{2.1}$$

where $e_{i,t}(j)$ is the expenditure of the good (j) of the individual i, belonging to the cohort h at time t, $y_{i,t}$ is the corresponding disposable income of the i individual, and $s_{h,t}$ is a vector of socio-economic and demographic characteristic such as type of income, labour and marital

[12]The AD-HBS has been developed in a joint research framework between the Department of the Treasury of the Ministry of Economy and Finance and the Department of Economics and Law at Sapienza University of Rome.

[13]Nonetheless, this model specification is in general appropriate for a quasi-panel structure, with a very detailed disaggregation of consumer expenditures in a repeated cross section data-type structure. See Deaton (1985) for a discussion about this point.

status, geographical location, etc.

A general form of the Engel model is the following (the t time subscript is dropped):

$$log(e_{i,h}(j)) = \alpha_q(j) + \beta_q(j) log(y_i) + \sum_{l=1}^{L} \gamma_{q,l}(j) s_h + \epsilon_{i,q}(j) \tag{2.2}$$

where α is the intercept capturing the average expenditure for the generic j good; s is a vector of L socioeconomic variables to control for, mainly through dummies (e.g., unemployment, area of residence, familiar status, gender[14], age) or specific information (e.g., type of income); γ is the coefficient of the l-variable, and ϵ is an error term. This formulation enables us to capture the responsiveness of consumption across income distributions and different types of goods (durables, non-durables, and services) in the specified q-quantile.

In this formulation, $\beta_q(j)$ is the elasticity of consumption with respect to income at different points of the distribution and type of goods:

$$EIE_q(j) = \beta_q(j) = \frac{\Delta e(j)}{\Delta y_q} \frac{y_q}{e(j)} \tag{2.3}$$

In this context $\beta_q(j)$ indicates how much j-expenditure is likely to vary as a result of a variation in the q-quantile disposable income. This is not immediately comparable with such similar estimates of MPC in the literature (see, for example, Jappelli and Pistaferri (2006)) that considers absolute change in consumption resulting from changes in income.

More specifically, it is an indication of how much of each additional unit of income the individual in the s state is likely to purchase above what they usually spend for the good j. In this formulation, the model is able to shed light whether households in the lowest income quantiles exhibit higher EIEs, consistent with liquidity constraints, or whether variations in consumption behaviour are driven by geographic factors, such as regional differences in cost of living or cultural norms.

2.5.2 The Quantile Regression

A standard OLS regression is primarily run as a benchmark reference. Since there is a strong variability throughout the consumption and income distributions, the OLS estimator

[14]The variable *gender* is binary not due to the choice of the authors, but because of the sampling techniques of ISTAT.

is not able to properly account for this heterogeneity yielding to biased estimates. Results are reported in Appendix B1 and in Section 2.7 for a comparison across time with quintile regression.

Then, to estimate the variation in EIE across the income distribution, we employ Quantile Regression (QR)[15], as proposed by Misra and Surico (2014). QR allows us to model the conditional distribution of consumption expenditures, providing insights into the heterogeneity of responses that would be missed by traditional mean-based methods. This approach is particularly useful in the presence of skewed distributions, as is often the case with income and consumption in the AD-HBS dataset. Additionally, QR is robust to outliers and can estimate effects at various points of the income distribution, aligning well with the goals of our analysis. The estimation involves solving the QR minimisation problem for a set of quantiles, providing a comprehensive view of the conditional distribution. Given the non-differentiability of the objective function, numerical methods like linear programming are employed.

To estimate the EIE we use the (conditional) quantile regression, in which the minimisation of asymmetrically weighted absolute residuals give the quantiles.

Specifically, to estimate the parameters, QR minimises the following objective function:

$$\hat{\beta}(\tau) = \arg\min_{\beta} \sum_{i=1}^{n} \rho_\tau(y_i - x_i'\beta),$$

where the check function $\rho_\tau(u)$ is defined as:

$$\rho_\tau(u) = u(\tau - \mathbf{1}_{\{u<0\}}).$$

This asymmetric weighting ensures that deviations below and above the quantile of interest are weighted differently.

The first-order conditions of this minimisation problem yield:

$$\frac{1}{n}\sum_{i=1}^{n} x_i \left(\tau - \mathbf{1}_{\{y_i - x_i'\beta(\tau)<0\}}\right) = 0,$$

which implies that the residuals are balanced around the τ-th quantile.

For the empirical model of consumption expenditure, the QR specification can be written

[15]The estimation methodology is based on the seminal works on Quantile Regression originally proposed by Koenker and Bassett (1978, 1982) and further explained in Koenker (2005).

as:

$$Q_{\ln(e_{i,h,t(j)})}(\tau|y,s) = \alpha_\tau(j) + \beta_\tau(j)\ln(y_{i,t}) + \sum_{l=1}^{L}\gamma_{l,\tau}(j)s_{h,t},$$

where: $\alpha_\tau(j)$ is the quantile-specific intercept, $\beta_\tau(j)$ is the income elasticity at the τ-th quantile, and $\gamma_{l,\tau}(j)$ captures the effects of socio-economic covariates.

Finally, we address potential biases arising from measurement errors or unobserved heterogeneity through robustness checks and alternative specifications. These include bootstrapped standard errors to account for sampling variability and inclusion or omission of terms to capture non-linear effects of income and demographic characteristics (see Appendix B3).

2.6 Quantifying EIE Heterogeneity

In this this section, we present evidence of significant heterogeneity in the EIEs along two dimensions. In paragraph 2.6.1 we provide EIE estimates controlling for socioeconomic and demographic factors but offsetting differences related to the type of goods. In paragraph 2.6.2 we analyse how EIEs differ across across expenditure categories (services, non-durables and durables).

2.6.1 EIE Heterogeneity: The Role of Socio-Economic Variables and Demographic Factors

In the first regression analysis (baseline estimates), we focus on the estimation of the EIEs regardless of the type of goods considered. We thus take the model (2.5.1), which has been aggregated over the goods j. In this case, the model becomes:

$$log(e_{i,h}) = \alpha_q + \beta_q log(y_i) + \sum_{l=1}^{L}\gamma_{q,l}s_h + \epsilon_{i,q} \tag{2.4}$$

where the coefficients have the same meaning, but now they refer to aggregate expenditure without any distinction across the goods. The coefficients still represent the same variables but now related to the total expenditure of all items without any differentiation across the $j-$type goods.

Table 2.4 reports the results of quantile regressions for aggregate expenditure in 2022, allowing for an examination of EIE heterogeneity across the income distribution while con-

trolling for socio-economic and demographic covariates. These variables, which include labour-market status (employed, unemployed, pensioner), household size and composition, age and marital status, home-ownership, and macro-area fixed effects, are jointly significant at conventional levels and absorb systematic compositional differences. In this sense, their inclusion preserves the qualitative pattern of a declining EIE across quantiles while slightly attenuating magnitudes, suggesting that heterogeneity is preserved even conditional on these observables. The dependent variable is the log of consumption expenditure. While in the text we present the results based on income deciles, the corresponding estimates based on quintiles are in Appendix B1. In particular, the specification includes dummies for the labour status (unemployed and retired), demographic variables (gender, familial status, age, family size), socioeconomic factors (foreign born and type of labour contract - permanent versus fixed term), dummies for households residence (North and South), and for city size (urban). Almost all the coefficients are statistically different from zero at 1%.

Specifically, the results reveal that EIE decreases monotonically across quantiles, reflecting a declining elasticity as income rises. In particular, the elasticity at the 10^{th} percentile ($q10$) is 0.203 ($SE = 0.005$), while at the 90^{th} percentile ($q90$) it falls to 0.146 ($SE = 0.003$), recording a negative variation by roughly 5.7 percentage points. Interestingly, the strongest decline occurs at high levels of income (by 1.2 percentage point decline between the seventh and eighth deciles). This downward trend in EIE across quantiles (deciles) is consistent with empirical evidence that lower-income households exhibit higher sensitivity of consumption to income changes, theoretically attributed to liquidity constraints and limited access to credit markets in theoretical models (see Deaton (1991) and more recently Kaplan et al. (2014) for providing foundational theoretical grounding of the classical model of liquidity-constrained consumption responses). Empirically, this result is consistent with Misra and Surico (2014) who document a similar pattern across income quantiles using quantile regression techniques for the US and Jappelli and Pistaferri (2014) who show such a similar behaviour for reported MPC in Italy.

Conditional on disposable income at each quantile, the covariate coefficients capture partial associations with expenditure. Specifically, labour market indicators proxy both the composition of resources (e.g., unemployment insurance, pensions) and life-cycle position (namely, young for unemployed and old for retired). The unemployment dummy is positive and statistically significant at all quantiles: 0.129 ($SE = 0.024$) at $q10$; 0.136 ($SE = 0.026$) at $q50$; 0.101 ($SE = 0.034$) at $q90$, with the largest association around the median.

Table 2.4: Decile regression Results: aggregate expenditure (2022)

Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90
log(Y)	0.203***	0.195***	0.194***	0.185***	0.185***	0.178***	0.168***	0.156***	0.146***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)
Unemployed	0.129***	0.102***	0.104***	0.104***	0.136***	0.107***	0.082***	0.106***	0.101***
	(0.024)	(0.022)	(0.027)	(0.021)	(0.026)	(0.020)	(0.027)	(0.031)	(0.034)
Retired	-0.073***	-0.086***	-0.079***	-0.077***	-0.075***	-0.080***	-0.085***	-0.098***	-0.093***
	(0.013)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.013)	(0.012)	(0.016)
Urban	0.089***	0.094***	0.102***	0.100***	0.095***	0.095***	0.085***	0.096***	0.092***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
Male	-0.017***	-0.018***	-0.019***	-0.018***	-0.017***	-0.015***	-0.013**	-0.014**	-0.006
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
Married	0.102***	0.098***	0.089***	0.091***	0.085***	0.067***	0.064***	0.067***	0.054***
	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.011)	(0.012)
Age (<30)	0.126***	0.124***	0.119***	0.115***	0.122***	0.100***	0.097***	0.073***	0.075***
	(0.016)	(0.015)	(0.015)	(0.014)	(0.016)	(0.014)	(0.015)	(0.017)	(0.022)
Age (30-50)	0.115***	0.092***	0.089***	0.080***	0.069***	0.063***	0.064***	0.033**	0.039**
	(0.015)	(0.014)	(0.013)	(0.012)	(0.013)	(0.013)	(0.014)	(0.015)	(0.019)
Age (51-65)	0.099***	0.094***	0.089***	0.086***	0.089***	0.089***	0.097***	0.072***	0.076***
	(0.013)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.017)
Foreign-born	-0.310***	-0.330***	-0.323***	-0.310***	-0.286***	-0.278***	-0.267***	-0.250***	-0.237***
	(0.014)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.012)	(0.014)	(0.012)
Fixed-term contract	0.034***	0.049***	0.053***	0.063***	0.077***	0.086***	0.098***	0.114***	0.093***
	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)	(0.009)
Family size (2)	-0.380***	-0.382***	-0.374***	-0.364***	-0.351***	-0.338***	-0.353***	-0.370***	-0.356***
	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.012)	(0.014)	(0.016)
Family size (3)	-0.591***	-0.603***	-0.593***	-0.585***	-0.584***	-0.568***	-0.586***	-0.601***	-0.613***
	(0.013)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.012)	(0.014)	(0.017)
Family size (4)	-0.759***	-0.756***	-0.747***	-0.733***	-0.727***	-0.720***	-0.746***	-0.770***	-0.782***
	(0.014)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.013)	(0.016)	(0.017)
Family size (5+)	-0.989***	-0.951***	-0.936***	-0.928***	-0.916***	-0.893***	-0.923***	-0.936***	-0.920***
	(0.018)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.015)	(0.017)	(0.018)
North	0.028***	0.037***	0.043***	0.041***	0.040***	0.039***	0.041***	0.040***	0.036***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)
South	-0.255***	-0.242***	-0.221***	-0.224***	-0.210***	-0.190***	-0.175***	-0.155***	-0.149***
	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.010)	(0.010)
constant	7.377***	7.643***	7.768***	7.958***	8.065***	8.241***	8.476***	8.767***	9.077***
	(0.051)	(0.042)	(0.036)	(0.040)	(0.039)	(0.040)	(0.046)	(0.050)	(0.039)
Pseudo-R^2	0.2632	0.2553	0.2472	0.2390	0.2320	0.2259	0.2186	0.2121	0.2077

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{tot})$ and the quantiles are 10 (decile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 53,310.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

This suggests that unemployed exhibit higher estimates compared to their employed counterparts, likely reflecting a stronger dependence on income to maintain consumption levels. This finding is consistent with theoretical predictions from Heterogeneous Agent New Keynesian (HANK) models, such as those proposed by Kaplan and Violante (2018), which emphasise the importance of liquidity constraints in amplifying consumption sensitivity. Empirical studies by Jappelli and Pistaferri (2006) and Krueger et al. (2016) further support this pattern, showing that unemployed households are more likely to be credit-constrained.

In contrast, retired individuals exhibit systematically negative and significant coefficients all over the deciles. The estimated coefficients range between -0.073 ($SE = 0.013$) at $q10$ and -0.093 ($SE = 0.016$) at $q90$. This negative relationship indicates lower consumption responsiveness among retired households, likely due to income smoothing facilitated by stable

pension transfers (see, for example, Gourinchas and Parker (2002)). For retired individuals, the lower consumption is likely due to income smoothing through stable pension transfers, as suggested by Jappelli (1990) and Blundell and Stoker (1999), other than precautionary savings (health) or bequest motives, either altruistic (Becker, 1981) or strategic (Bernheim et al., 1985).

Urban residency is positively associated with consumption across the income distribution. The coefficients remain stable and significant, ranging from 0.089 ($SE = 0.006$) at $q10$ to 0.102 ($SE = 0.005$) at $q30$, underscoring the role of location. This finding might be explained by the fact that urban residents usually experience better access to provision of services and financial institutions, enhancing their ability to consume in response to income changes (see Blundell et al. (2008)).

Gender reveals a small but significant negative effect for males, particularly at lower deciles. The coefficient for males at $q10$ is -0.017 ($SE = 0.006$), with the magnitude decreasing across quantiles and becoming statistically insignificant at $q90$. This result reveals gender differences in expenditures, once income is controlled for each quantile. These differences may stem from variations in financial risk tolerance and income allocation, as discussed by Croson and Gneezy (2009), who highlight different risk-taking behaviours, potentially influencing consumption decisions.

Marital status is positively associated with consumption, with married individuals exhibiting significant coefficients that decline across the distribution, from 0.102 ($SE = 0.009$) at $q10$ to 0.054 ($SE = 0.012$) at $q90$. About this effect, the results in literature are mixed and inconclusive. On the one hand, this evidence is in contrast with Lise and Seitz (2011) who supports the notion that married couples may allocate income more efficiently, thereby enhancing their ability to adjust consumption in response to income changes; on the other hand, other factors might impact the marital status on savings and portfolio choices (such as divorce or widowhood), often leading to decreased savings and altered investment behaviours (see Love (2010)).

Age group effects show a declining pattern in each quantiles meaning that younger individuals (< 30) exhibit significantly higher estimates than the older counterparts, with coefficients of 0.126 ($SE = 0.016$) at $q10$ and 0.075 ($SE = 0.022$) at $q90$. This finding suggests that younger individuals are more likely to face liquidity constraints, leading to higher sensitivity to income changes (see Jappelli and Pistaferri (2006)). Additionally, Carroll and Kimball (1996) suggest that younger individuals typically have lower accumulated wealth

and greater borrowing needs, increasing their marginal propensity to consume. Similar, but less pronounced, patterns are observed for individuals aged 30–50 and 51–65, consistent with the life-cycle hypothesis, which posits that consumption elasticity declines with age as households accumulate assets and smooth consumption over time (see Modigliani and Brumberg (1954)).

Foreign-born individuals exhibit lower estimates, as reflected in negative coefficients for the foreign-born variable across all quantiles. This may indicate that foreign-born individuals save more relative to their Italian counterparts, potentially reflecting higher precautionary savings due to greater income instability, weaker social safety nets, or the need to remit money to families abroad. Dustmann and Görlach (2016) emphasise the role of economic uncertainty and migration-related factors in shaping the saving behaviours of immigrants. Furthermore, evidence from Jappelli and Pagano (1994) highlights how liquidity constraints may differ between native and foreign-born populations, with the latter often resorting to savings as a buffer against economic shocks.[16]

The results for the fixed-term contract dummy provide insights into the consumption behaviour of workers with potentially limited financial stability. Across all deciles, the fixed-term contract variable is positive and statistically significant, indicating that individuals with fixed-term contracts exhibit higher coefficients compared to their counterparts on permanent contracts (the baseline group), once income is controlled for. This finding aligns with the hypothesis that fixed-term workers in Italy are more likely to face liquidity constraints, limiting their ability to smooth consumption over time. The lack of access to stable credit systems, coupled with income uncertainty associated with temporary employment, likely drives this higher sensitivity to consumption (see ECB (2020) for the European Union and De Lucia and Meacci (2005) for Italy).

Family size exerts a strong negative effect on consumption elasticity across all deciles. Larger households (e.g., 5+ components) exhibit coefficients of -0.989 ($SE = 0.018$) at $q10$ and -0.920 ($SE = 0.018$) at $q90$, reflecting economies of scale in consumption, where per capita resource needs diminish with larger household sizes due to shared goods and services. This is consistent with Deaton and Paxson (1998) that found that per capita food consumption decreases as household size increases and Gan and Vernon (2003) found that larger households tend to allocate a smaller proportion of their budget to certain goods,

[16] Additionally, cultural differences in consumption habits and financial priorities could also explain the observed patterns.

further indicating significant economies of scale in larger families.

The geographical location dummies play a crucial role in controlling for different consumption behaviours, revealing noticeable disparities across Italian regions. The positive and statistically significant coefficients for the *North* dummy across all deciles indicate that households in the *North* exhibit higher responsiveness compared to the *Centre* (the baseline group). This result could reflect higher economic opportunities, greater access to services, or cultural norms favouring consumption in the North as opposed to the *South* dummy as documented in Accetturo et al. (2022). See Appendix B2 for regression results on specific areas (North, Centre and South) and city size (urban and rural).

2.6.2 The EIE across Expenditure Categories: Services, Durables and Non-Durables

In the previous section, we have documented strong evidence of heterogeneous EIEs in presence of socio-economic and demographic factors. In this paragraph we provide some further EIEs estimates across different types of goods - durables, non-durables, and services. Such differentiation is important to understand how income variations shape different consumption patterns, in a way reflecting another relevant source of EIE heterogeneity. As for the previous paragraph, we have investigated the EIE heterogeneity focusing exclusively on the last available year in the AD-HBS dataset (2022).

In literature the empirical relevance of such heterogeneity is captured, among others, by Misra and Surico (2014) who show and quantify the distinct patterns of EIE responses for durables and non-durables, somehow emphasising the need for disaggregated analysis. In the traditional interpretation, services often reflect basic needs (e.g., housing and healthcare), while durables represent long-term investments, and non-durables typically align with day-to-day necessities.

Table 2.5 shows the different types of expenditures collected in the AD-HBS dataset, following the COICOP-18 classification. They are further aggregated into the canonical tripartition of services, durable and non-durable goods. Overall, the expenditures for services cover more than the half of total budget (53.3%); the remaining part is devoted to good consumption, durables (25.1%) and non-durables (21.6%) with similar shares.[17]

Table 2.6 shows the EIE estimates for services. By and large, services exhibit qualitatively

[17]For further details, see Casalis and Krustev (2020).

Table 2.5: Lines of individual expenditure and aggregated groups (2022)

Category	Mean	Share	Group	Percentage
Utilities & Housing (rent)	5,181.84	0.3638	Services	53.28%
Accommodation & Restaurant	779.43	0.0547		
Health	647.86	0.0455		
Recreational (sport, culture)	528.34	0.0371		
Finance & insurance	366.61	0.0257		
Education	84.17	0.0059		
Food	2,689.86	0.1889	Non-durables	25.13%
Care	655.28	0.0460		
Alcohol & Tobacco	233.40	0.0164		
Transport	1,530.40	0.1075	Durables	21.59%
Furniture	608.90	0.0428		
Clothing	556.87	0.0391		
Media & communication	379.03	0.0266		
Aggregate	14,241.98	1.0000	-	100.00%

Notes: *Mean* is individual average in €, *Share* is the fraction of total consumption. Lines are grouped according to the main category of reference (services, non-durables, durables), whilst none of them is entirely devoted to only one group. Data is from 2022.

the same type of relationship as the EIEs aggregate estimates, although values are slightly lower across most deciles and the rate of decline across deciles in services is steeper than the aggregate one as in Table 2.4. This pattern likely reflects the essential nature of many service expenditures, such as utilities and healthcare, which are less sensitive to income variations due to their necessity. This finding aligns with Misra and Surico (2014), who observe that basic services tend to show limited responsiveness to income changes. Interestingly, the EIE for services shows a relatively stable decline across income deciles, similar to the aggregate trend, indicating persistent heterogeneity driven by liquidity constraints at lower income levels. Specifically, unemployed individuals display a relatively higher coefficients for services (0.100 at $q10$, rising to 0.111 at $q80$), reflecting the prioritisation of essential services despite limited income. Retired households, however, exhibit consistently negative values across deciles (e.g., -0.076 at $q10$ and -0.088 at $q90$). Urban households exhibit significantly higher estimates for services across all deciles (e.g., 0.162 at $q90$ for urban households), compared to their non-urban counterparts. This difference underscores the role of urbanisation in shaping service consumption patterns, as urban areas typically have greater access to and higher costs for services like public transportation, healthcare, and education. Once accounting for income, households in Northern Italy show higher expenditures for services compared to those in the South (0.042 at $q10$ vs. -0.314). These regional differences likely stem

Table 2.6: Decile regression results: Services in 2022

Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90
log(Y)	0.183***	0.190***	0.190***	0.184***	0.178***	0.176***	0.173***	0.164***	0.149***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)
Unemployed	0.100***	0.107***	0.108***	0.105***	0.101***	0.090***	0.102***	0.111***	0.034
	(0.020)	(0.020)	(0.018)	(0.021)	(0.018)	(0.021)	(0.025)	(0.028)	(0.038)
Retired	-0.076***	-0.083***	-0.086***	-0.078***	-0.079***	-0.085***	-0.089***	-0.100***	-0.088***
	(0.014)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.012)	(0.014)	(0.017)
Urban	0.121***	0.128***	0.136***	0.147***	0.148***	0.153***	0.145***	0.150***	0.162***
	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)
Male	-0.022***	-0.027***	-0.029***	-0.022***	-0.020***	-0.019***	-0.022***	-0.017***	-0.011
	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
Married	0.067***	0.068***	0.069***	0.069***	0.068***	0.067***	0.063***	0.059***	0.061***
	(0.009)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.010)	(0.012)
Age (<30)	0.025	0.036***	0.040***	0.047***	0.038***	0.027**	0.026*	0.006	0.008
	(0.017)	(0.012)	(0.013)	(0.012)	(0.012)	(0.014)	(0.015)	(0.017)	(0.021)
Age (30-50)	0.032**	0.023**	0.021*	0.019*	0.005	-0.009	-0.015	-0.030*	-0.037**
	(0.015)	(0.011)	(0.012)	(0.011)	(0.010)	(0.012)	(0.013)	(0.016)	(0.019)
Age (51-65)	0.020	0.027***	0.029***	0.032***	0.026***	0.024**	0.024**	0.019	0.032**
	(0.014)	(0.010)	(0.010)	(0.010)	(0.009)	(0.011)	(0.012)	(0.014)	(0.016)
Foreign-born	-0.309***	-0.313***	-0.318***	-0.309***	-0.309***	-0.293***	-0.294***	-0.287***	-0.268***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.011)	(0.010)	(0.010)	(0.012)	(0.017)
Fixed-term contract	0.029***	0.046***	0.057***	0.070***	0.080***	0.092***	0.103***	0.113***	0.132***
	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)	(0.012)
Family size (2)	-0.449***	-0.450***	-0.453***	-0.453***	-0.451***	-0.442***	-0.434***	-0.425***	-0.427***
	(0.012)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)	(0.011)	(0.012)	(0.015)
Family size (3)	-0.726***	-0.715***	-0.721***	-0.725***	-0.722***	-0.713***	-0.713***	-0.706***	-0.705***
	(0.014)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.011)	(0.012)	(0.016)
Family size (4)	-0.908***	-0.903***	-0.903***	-0.903***	-0.897***	-0.882***	-0.883***	-0.875***	-0.877***
	(0.013)	(0.010)	(0.010)	(0.010)	(0.011)	(0.012)	(0.012)	(0.013)	(0.018)
Family size (5+)	-1.179***	-1.148***	-1.136***	-1.114***	-1.102***	-1.085***	-1.090***	-1.089***	-1.082***
	(0.017)	(0.013)	(0.014)	(0.012)	(0.013)	(0.014)	(0.014)	(0.016)	(0.025)
North	0.042***	0.056***	0.069***	0.063***	0.063***	0.065***	0.061***	0.064***	0.063***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.010)
South	-0.314***	-0.304***	-0.296***	-0.308***	-0.313***	-0.323***	-0.329***	-0.322***	-0.280***
	(0.008)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.009)	(0.012)
Constant	7.129***	7.206***	7.318***	7.470***	7.633***	7.761***	7.916***	8.148***	8.484***
	(0.053)	(0.038)	(0.040)	(0.034)	(0.036)	(0.039)	(0.035)	(0.039)	(0.053)
Pseudo-R^2	0.3528	0.3478	0.3404	0.3319	0.3223	0.3120	0.3002	0.2841	0.2607

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{services})$ and the quantiles are 10 (decile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 53,310.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

from variations in income levels, service accessibility, and cultural norms, as discussed by Accetturo et al. (2022).

The EIE for non-durables shown in Table 2.7 is lower than the aggregate elasticity for most deciles. Indeed, at the 10^{th} percentile ($q10$), the EIE for non-durables is 0.136, compared to 0.203 in the aggregate. This gap reflects the relatively inelastic nature of non-durable goods, which are essential and often constitute a stable portion of household expenditure. Similar to the aggregate one, the EIE for non-durables decreases across income deciles. However, the decline is less steep than in the aggregate: at the 90^{th} percentile ($q90$), the EIE for non-durables is 0.104, compared to 0.146 in the aggregate, suggesting that higher-income households are less likely to adjust their non-durable consumption proportionally with income changes. Unemployed individuals exhibit a higher expenditures for non-durables at the

Table 2.7: Decile regression results: Non-durables in 2022

Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90
log(Y)	0.136***	0.122***	0.116***	0.116***	0.107***	0.102***	0.100***	0.097***	0.104***
	(0.009)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)
Unemployed	0.143***	0.122***	0.058**	0.083**	0.085***	0.068***	0.044*	0.052	0.128***
	(0.049)	(0.032)	(0.026)	(0.034)	(0.032)	(0.025)	(0.026)	(0.035)	(0.044)
Retired	0.044*	0.008	0.000	0.006	-0.005	-0.012	-0.017	-0.020	-0.032
	(0.023)	(0.017)	(0.016)	(0.014)	(0.014)	(0.013)	(0.015)	(0.015)	(0.020)
Urban	0.000	0.026***	0.040***	0.047***	0.038***	0.038***	0.032***	0.030***	0.025**
	(0.011)	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.010)
Male	-0.021**	-0.028***	-0.021***	-0.018***	-0.017***	-0.013*	-0.017***	-0.016**	-0.030***
	(0.010)	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.010)
Married	0.075***	0.073***	0.061***	0.046***	0.039***	0.041***	0.034***	0.019*	0.029**
	(0.015)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.014)
Age (<30)	0.074**	0.049**	0.034*	0.033*	0.025	0.015	0.004	-0.018	0.006
	(0.029)	(0.021)	(0.019)	(0.017)	(0.017)	(0.016)	(0.020)	(0.019)	(0.026)
Age (30-50)	0.040	0.015	0.007	0.019	0.015	0.007	-0.014	-0.023	-0.020
	(0.027)	(0.019)	(0.017)	(0.016)	(0.016)	(0.015)	(0.018)	(0.017)	(0.024)
Age (51-65)	0.140***	0.092***	0.066***	0.070***	0.070***	0.056***	0.043***	0.039***	0.030
	(0.022)	(0.017)	(0.016)	(0.014)	(0.014)	(0.012)	(0.015)	(0.015)	(0.021)
Foreign-born	-0.282***	-0.271***	-0.247***	-0.220***	-0.218***	-0.218***	-0.202***	-0.197***	-0.177***
	(0.024)	(0.016)	(0.015)	(0.012)	(0.012)	(0.014)	(0.013)	(0.013)	(0.018)
Fixed-term contract	0.019	-0.002	0.007	0.015	0.033***	0.034***	0.041***	0.062***	0.065***
	(0.018)	(0.015)	(0.011)	(0.010)	(0.009)	(0.009)	(0.011)	(0.012)	(0.014)
Family size (2)	-0.135***	-0.192***	-0.201***	-0.219***	-0.226***	-0.248***	-0.263***	-0.277***	-0.331***
	(0.022)	(0.017)	(0.014)	(0.015)	(0.013)	(0.013)	(0.013)	(0.015)	(0.021)
Family size (3)	-0.292***	-0.338***	-0.342***	-0.369***	-0.402***	-0.429***	-0.436***	-0.444***	-0.536***
	(0.025)	(0.018)	(0.016)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.021)
Family size (4)	-0.383***	-0.462***	-0.493***	-0.524***	-0.556***	-0.579***	-0.598***	-0.625***	-0.727***
	(0.026)	(0.018)	(0.017)	(0.016)	(0.015)	(0.016)	(0.016)	(0.015)	(0.023)
Family size (5+)	-0.497***	-0.603***	-0.634***	-0.675***	-0.707***	-0.724***	-0.718***	-0.743***	-0.803***
	(0.029)	(0.021)	(0.019)	(0.019)	(0.017)	(0.020)	(0.019)	(0.018)	(0.027)
North	-0.030**	-0.037***	-0.029***	-0.019**	-0.002	0.002	-0.007	-0.015*	-0.004
	(0.014)	(0.011)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)	(0.011)
South	-0.100***	-0.094***	-0.063***	-0.032***	-0.015*	0.001	0.003	0.025**	0.064***
	(0.015)	(0.011)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.013)
Constant	6.105***	6.628***	6.890***	7.043***	7.290***	7.494***	7.695***	7.933***	8.175***
	(0.090)	(0.057)	(0.054)	(0.052)	(0.047)	(0.042)	(0.046)	(0.039)	(0.062)
Pseudo-R^2	0.0637	0.0737	0.0805	0.0851	0.0884	0.0907	0.0943	0.0961	0.0969

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{nondurables})$ and the quantiles are 10 (decile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 53,118.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

lower deciles (e.g., 0.143 at $q10$), reflecting prioritisation of basic needs under constrained budgets. This finding supports empirical evidence by Krueger et al. (2016) on higher sensitivity among liquidity-constrained groups. Urban households exhibit slightly higher estimates for non-durables across mid-to-upper deciles, presumably suggesting greater responsiveness in areas with higher costs of living or more consumption opportunities, while households in Northern Italy exhibit marginally higher coefficients for non-durables compared to those in the South.

EIE for durable goods are presented in Table 2.8. It is substantially higher at the lower income deciles compared to the aggregate EIE. These findings corroborate the insights of Kaplan et al. (2014), who emphasise the role of durables in amplifying EIE heterogeneity due to their lump-sum nature and credit-driven accessibility. For instance, at the 10^{th}

Table 2.8: Decile regression results: Durables in 2022

Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90
log(Y)	0.363***	0.311***	0.284***	0.261***	0.254***	0.245***	0.232***	0.211***	0.200***
	(0.014)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Unemployed	0.303***	0.148***	0.119***	0.098**	0.088	0.158***	0.139***	0.083	0.185***
	(0.083)	(0.057)	(0.041)	(0.038)	(0.057)	(0.044)	(0.038)	(0.059)	(0.062)
Retired	-0.279***	-0.224***	-0.226***	-0.208***	-0.173***	-0.175***	-0.154***	-0.178***	-0.164***
	(0.043)	(0.030)	(0.025)	(0.022)	(0.022)	(0.023)	(0.025)	(0.025)	(0.033)
Urban	-0.013	0.005	0.022**	0.029***	0.034***	0.034***	0.046***	0.040***	0.022*
	(0.018)	(0.013)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.012)	(0.013)
Male	0.002	0.015	0.030***	0.019**	0.012	0.016*	0.014	0.017	0.010
	(0.017)	(0.013)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.012)	(0.013)
Married	0.251***	0.186***	0.163***	0.154***	0.143***	0.123***	0.123***	0.103***	0.084***
	(0.026)	(0.017)	(0.015)	(0.014)	(0.015)	(0.014)	(0.014)	(0.017)	(0.024)
Age (<30)	0.696***	0.573***	0.490***	0.462***	0.436***	0.393***	0.395***	0.300***	0.263***
	(0.053)	(0.038)	(0.034)	(0.027)	(0.028)	(0.028)	(0.030)	(0.031)	(0.039)
Age (30-50)	0.577***	0.514***	0.433***	0.394***	0.378***	0.344***	0.330***	0.247***	0.239***
	(0.046)	(0.034)	(0.030)	(0.024)	(0.024)	(0.025)	(0.027)	(0.028)	(0.034)
Age (51-65)	0.538***	0.452***	0.366***	0.331***	0.314***	0.297***	0.307***	0.241***	0.205***
	(0.042)	(0.029)	(0.026)	(0.022)	(0.020)	(0.022)	(0.025)	(0.025)	(0.030)
Foreign-born	-0.554***	-0.456***	-0.424***	-0.357***	-0.324***	-0.267***	-0.258***	-0.251***	-0.209***
	(0.049)	(0.024)	(0.020)	(0.022)	(0.024)	(0.019)	(0.019)	(0.022)	(0.031)
Fixed-term contract	0.123***	0.112***	0.120***	0.132***	0.130***	0.133***	0.139***	0.107***	0.121***
	(0.025)	(0.018)	(0.015)	(0.015)	(0.015)	(0.015)	(0.017)	(0.018)	(0.022)
Family size (2)	-0.108***	-0.062**	-0.119***	-0.152***	-0.181***	-0.173***	-0.213***	-0.245***	-0.273***
	(0.037)	(0.029)	(0.023)	(0.021)	(0.018)	(0.019)	(0.021)	(0.025)	(0.031)
Family size (3)	-0.173***	-0.204***	-0.290***	-0.335***	-0.352***	-0.368***	-0.405***	-0.433***	-0.507***
	(0.039)	(0.029)	(0.024)	(0.022)	(0.021)	(0.020)	(0.021)	(0.026)	(0.033)
Family size (4)	-0.169***	-0.254***	-0.343***	-0.406***	-0.460***	-0.477***	-0.525***	-0.543***	-0.627***
	(0.042)	(0.031)	(0.025)	(0.022)	(0.022)	(0.022)	(0.023)	(0.027)	(0.035)
Family size (5+)	-0.528***	-0.510***	-0.535***	-0.608***	-0.599***	-0.596***	-0.663***	-0.632***	-0.767***
	(0.052)	(0.037)	(0.028)	(0.025)	(0.027)	(0.024)	(0.026)	(0.030)	(0.036)
North	-0.085***	-0.069***	-0.038***	0.000	0.012	0.015	0.033***	0.073***	0.098***
	(0.021)	(0.015)	(0.013)	(0.011)	(0.011)	(0.012)	(0.011)	(0.014)	(0.016)
South	-0.298***	-0.258***	-0.208***	-0.174***	-0.152***	-0.141***	-0.111***	-0.103***	-0.105***
	(0.024)	(0.017)	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.019)
constant	2.803***	3.833***	4.475***	4.969***	5.267***	5.590***	5.947***	6.506***	7.090***
	(0.140)	(0.087)	(0.079)	(0.071)	(0.069)	(0.077)	(0.073)	(0.075)	(0.094)
Pseudo-R^2	0.0832	0.0758	0.0719	0.0702	0.0688	0.0673	0.0654	0.0650	0.0695

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{durables})$ and the quantiles are 10 (decile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 53,060.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

percentile ($q10$), the EIE for durables is 0.363, significantly exceeding the aggregate one of 0.203. This disparity reflects the nature of durable goods as lump-sum investments, with low-income households likely delaying such purchases until income shocks allow for these expenditures. The decline in EIE for durables across income deciles is more pronounced than for the aggregate one. At the 90^{th} percentile ($q90$), the EIE for durables drops to 0.200, whereas the aggregate one decreases to 0.146. This steep decline suggests that higher-income households allocate a smaller proportion of additional income to durables, consistent with the saturation effect observed in discretionary consumption. While the unemployed coefficient displays higher estimate values for durables, particularly at lower deciles (0.303 at $q10$), urban households exhibit higher levels for durables at mid-to-high deciles (e.g., 0.046 at $q70$), likely reflecting greater access to credit and a broader range of consumption

opportunities in urban settings, while younger households (< 30) show the highest values for durables across deciles, such as 0.696 at $q10$, being likely to reflect life-cycle factors and the need to establish durable goods early in their economic life-cycle.

In Appendix B2, to have a glance to the evolution over time, estimates of previous years are reported: Table B2.6 for services, Table B2.7 for non-durables, and Table B2.8 for durables.

2.7 The EIE across time and the Covid Crisis

In the previous sections we have investigated the EIE heterogeneity basically focusing exclusively on the last available year in the AD-HBS dataset (2022). In this section, we extend the analysis to other previous available years (2018-2021) for understanding how consumption patterns evolve in response to changing economic conditions, such as policy interventions or external shocks like the COVID-19 pandemic or the Russia-Ukraine war in 2022. This type of analysis enables both a better understanding of the persistence of heterogeneity in EIE and an assessment of the stability of observed behaviour across varying social-economic conditions, offering a more comprehensive perspective of the estimates presented in the previous sections. It is worth noticing that the sample covers periods of exceptional macroeconomic stress (2019–2022), which are typically set aside in studies focusing on times of relative stability but are crucial for understanding how expenditure responds when the socio-economic environment changes. In light of ongoing geopolitical and macro-financial risks (e.g., the war in Ukraine, the humanitarian crisis in Gaza, shifting trade policy, and reserve-currency uncertainty), any projection based on 2019–2022 should explicitly acknowledge a substantial degree of uncertainty. We therefore interpret our EIEs as elasticities conditional on the prevailing risk environment rather than structural constants.[18]

Indeed, we estimate the EIE before and after the introduction of the *Reddito di Cittadinanza* in April 2019; we also analyse the subsequent economic disruptions caused by the COVID-19 pandemic in 2020-2021: this period was marked by widespread economic uncertainty, restrictions on consumption opportunities, and precautionary savings behaviour. As highlighted by Jappelli and Pistaferri (2020), the pandemic created unprecedented uncer-

[18]Section 2.8 shows that changes in the composition of idiosyncratic income risk — especially lower persistence and volatility of the near-permanent component — reduce the present-value multiplier and dampen the pass-through from income to expenditure; this mechanism rationalises the 2020–2022 compression in EIEs and provides a natural basis for scenario-based projections going forward.

tainty regarding future income, employment, and economic stability, prompting households to adopt precautionary savings behaviours.[19] The Russia-Ukraine war in 2022 triggered further economic instability due to the energy crisis.

Table 2.9: Quintile Estimates (2018–2022)

Quintile	2018	2019	2020	2021	2022	Drop (2020)	Drop (2022)
q20	0.231	0.242	0.182	0.210	0.195	-24.8%	-19.4%
q40	0.197	0.220	0.169	0.201	0.185	-23.1%	-15.9%
q60	0.182	0.185	0.168	0.187	0.178	-9.4%	-3.8%
q80	0.168	0.158	0.155	0.174	0.156	-1.8%	-1.3%
OLS	0.183	0.182	0.164	0.183	0.169	-10.0%	-7.0%

Notes: Estimation performed using a conditional quantile regression with 500 bootstrap replications. Drops (2020, 2022) are percentage deviations relative to the year 2019. The dependent variable is $log(C_{tot})$ and the quantiles are 5 (quintile). Here reported only coefficients of $log(Y)$, but the variable selection is the same as previously done for the other models (see Appendix B1 for complete regressions of OLS and Quintiles). Figure B1.3 resumes the table.

Table 2.9 presents the EIE estimates over time and across quintiles.[20] The results reveal significant shifts influenced by key economic events, including the introduction of the *Reddito di Cittadinanza* (RdC) in 2019, the COVID-19 crisis in 2020 and the Russia-Ukraine war in 2022. Figure B1.3 (in Appendix B1) sketches graphically the Table 2.9.

The introduction of RdC, a minimum income scheme aimed at supporting low-income households, contributed to a moderate increase in EIE in 2019 relative to 2018, particularly among lower-income quintiles ($q20$ and $q40$). This policy likely increased disposable income for vulnerable households, enabling higher consumption responsiveness to income changes. This effect is evident in the slight upside in EIE values from 2018 to 2019 across the lower and middle quintiles, such as $q20$ and $q40$, which rose by 4.8% and 11.7%, respectively. This pattern is consistent with theories emphasising the higher consumption responsiveness of liquidity-constrained households. However, the programme's impact diminishes at higher income levels, as wealthier households are less reliant on current income for consumption.

In contrast, the onset of the COVID-19 pandemic in 2020 marks a sharp departure from the trends observed in previous years, with EIE values plummeting across all income

[19]Furthermore, lockdown measures and social distancing severely limited spending opportunities, particularly for discretionary and durable goods, thereby reducing overall consumption responsiveness. For many households, income levels were directly affected by job losses, furloughs, or reduced working hours, further constraining consumption.

[20]The estimates for 2022 are consistent with those presented in the previous sections here reported for completeness.

quintiles. The decline was most pronounced in the low-middle income brackets, such as $q20$ and $q40$, which experienced reductions of 24.8% and 23.1% relative to 2019, respectively. This result is consistent with Immordino et al. (2024) and Immordino et al. (2022) highlighting the COVID-19 pandemic effects on consumption behaviour, particularly among low-income households. Furthermore, the observed decline is in line with theoretical expectations that households increase savings during economic downturns, particularly when future income prospects are uncertain. Interestingly, the highest income quintiles exhibited a relatively smaller drop in EIE, likely reflecting greater financial resilience and less reliance on current income for consumption.

The recovery in EIE observed in 2021, albeit partial, indicates a gradual normalisation of consumption patterns as a result of stabilisation schemes, as pandemic-related restrictions eased and household confidence improved. In 2021, EIE values remained below pre-pandemic (2018-2019) levels for most quintiles, particularly at lower income levels. This persistence in the aftermath of the pandemic suggests that this crisis induced structural changes in consumption behaviour, with wealthier households potentially adopting more conservative spending habits. Low-middle income households, which bore the brunt of income and consumption shocks during the pandemic, showed an incomplete recovery, while wealthier brackets roughly restored the pre-crisis levels of EIEs.

The decline in the Expenditure-Income Elasticity (EIE) observed in 2022 across all quintiles, as shown in Table 2.9, can be attributed to the economic instability triggered by the Russia-Ukraine war. This conflict induced several economic disruptions that significantly affected household behaviour along several dimensions, it primarily led to a surge in energy prices, with natural gas and oil prices reaching unprecedented levels in 2022.[21] For many households, particularly in Europe, this meant increased expenditures on energy bills, leaving less disposable income for other consumption. Recent literature highlights how rising energy costs disproportionately affect middle- and low-income households (see, among others, technical reports and institutional studies as Menyhért (2022), Vidal Lorda and Villani (2022), Fulvimari et al. (2023), Corsello and Riggi (2023)), leading to reduced discretionary spending and lower EIEs .

[21] Inflationary pressures eroded real incomes, especially for lower-income groups. While nominal incomes might have remained stable or even increased slightly due to government interventions, the purchasing power of households diminished significantly.

2.8 Heterogeneity in Income Shocks

The results in the previous section highlighted the role of the EIE heterogeneity in several years characterized by different policy interventions and socio-economic conditions. Nevertheless, Table 2.9 shows that the relevant source of heterogeneity in EIE, namely its decreasing pattern across quantiles, holds regardless of the year considered.[22]

However, given the number of income shocks occurring over the sample considered (2018-2022), one may wonder whether the empirical results are consistent with an inter-temporal consumption behaviour and how the composition of temporary (low-persistent) and permanent (high-persistent) income changes might vary during this time span. We answer this question through the lenses of the Aiyagari (1994) model featuring heterogenous households solving a standard intertemporal optimization problem with Constant Relative Risk Aversion (CRRA) instantaneous utility function. They face a borrowing constraint preventing wealth from being negative and idiosyncratic risk on their income made up of the sum of two stochastic components: an high-persistent AR(1) process, representing the permanent component of idiosyncratic earnings (a near–unit-root shock that shifts lifetime resources), and a low-persistent AR(1) process, that is a transitory disturbance with short memory (e.g., bonuses, short-time policy schemes, temporary lay-offs, or measurement error).[23] After solving the model under a standard calibration of the relevant parameters (discount factor by 0.95, an interest rate of 2 percent and household risk aversion of CRRA preferences by 2) we estimate the two shocks (their persistence ρ and standard deviation σ) to ensure that the model can replicate the quantitative pattern of EIE heterogeneity as seen in empirical estimates of Table 2.9. In this way the model enables the identification of driving income shocks based on constraints imposed by the model equations, i.e. by economic theory, across variables and over time. The ability of these shocks to jointly fit the estimates EIEs and their co-movements across the quintiles determines the composition (permanent vs temporary) and size of the different shocks for every year.

Specifically, we calibrate the income–shock process to match targeted subsamples of the empirical EIE estimates in Table 2.9, corresponding to three distinct macro environments: (i) 2018–2019, a relatively stable period that includes the introduction of the *Reddito di Cittadinanza*; (ii) 2020–2021, marked by large income disruptions associated with the COVID–19

[22] In Section 2.10 we show that this result is quite robust to the inclusion of control variables, the methodology used and different sample selections.

[23] For more information about the model and the shock estimation strategy see Appendix B6.

Table 2.10: Estimated shock parameters by period

	2018–2019		2020–2021		2022	
Shock	ρ	σ	ρ	σ	ρ	σ
High-persistent	0.9223	2.5511%	0.8893	2.1700%	0.9091	2.3484%
Low-persistent	0.0185	0.0910%	0.0186	0.0873%	0.0186	0.0871%

Notes: ρ is the persistence parameter; σ is the shock standard deviation (percent).

pandemic;[24] and (iii) 2022, shaped by international tensions in energy markets following the Russia–Ukraine war.

The model-implied targets are computed from simulated EIEs. In this approach, the mapping is disciplined by minimising the quadratic distance between model–implied and observed EIE profiles. In more details, we generate a quasi-random (quasi-Montecarlo) sequence of initial values to create a grid of pseudo-parameters eligible for the solution of the minimisation problem. We then use this grid to run several trials and compute the quadratic deviation of the associated moments from the empirical ones. We then select the parameters associated with the trial having the smallest residual.

Table 2.10 reports the period–specific parameters of the two–shock income process obtained by matching simulated EIEs to their empirical counterparts across quintiles.

Within the Aiyagari (1994) framework the persistence of the near–permanent component, ρ, operates through the present–value multiplier given by $1/(1-\rho/R)$:[25] a lower ρ compresses the multiplier and dampens the consumption pass–through of income changes.

By contrast, the variance of the permanent component helps pin down the overall level and slope of EIEs across the resource distribution, while the transitory variance governs curvature via precautionary motives (higher transitory risk raises buffer–stock saving and lowers the local EIEs). Consistent with these mechanisms, the high–persistent component displays a compression in 2020–2021 relative to 2018–2019 - its persistence falls from $\rho = 0.9223$ to $\rho = 0.8893$ and its standard deviation from 2.55% to 2.17% - whereas the

[24] To stabilise household incomes during the pandemic shock, the Italian Government relied on automatic stabilisers and extraordinary support measures, including wage-supplementation schemes (CIG), unemployment benefits (NASpI, DIS-COLL), minimum-income transfers (ReI in 2018 and, from 2019, RdC), and family allowances (ANF), together with other public transfers recorded in the administrative data.

[25] By present–value multiplier we mean the effect of a unit innovation in the persistent income component on lifetime resources when income follows an AR(1). If the gross real return is R and persistence is ρ, the expected discounted path is $\sum_{j=0}^{\infty}(\rho/R)^j = 1/(1-\rho/R)$ for $|\rho| < R$. A lower ρ (or higher R) reduces this multiplier and, with an annuity-type pass–through from wealth to consumption, implies a smaller impact response of expenditure. See Appendix B6 for more details.

transitory component remains essentially unchanged ($\rho \simeq 0.019$, $\sigma \simeq 0.09\%$). The joint fall in ρ and σ for the high–persistent shock in 2020–2021 therefore rationalises the downward shift of the EIE profile documented in the data for that period (see Table 2.9). Within this structural interpretation through the lenses of the model, results suggest that intertemporal movements in the EIE are primarily driven by the near–permanent component: when both its persistence and variance fall, the income-to-expenditure pass-through declines broadly across the distribution. This pattern is consistent with stronger insurance against permanent income drop during the pandemic period (e.g., automatic stabilisers and programme support) and helps rationalise the compression of EIEs via a smaller present-value impact of shocks. In this sense, in 2022 the permanent parameters partially rebound ($\rho = 0.9091$, $\sigma = 2.35\%$) but do not return to pre–pandemic levels. Indeed, the partial normalisation of the near–permanent parameters in 2022 accounts for the observed but incomplete recovery of elasticities.

Taken together, our evidence delivers two messages. First, movements in the near-permanent income component are the key driver of the heterogeneous expenditure response: in 2020–2021 we estimate a decline in both its persistence and variance, which, via a smaller present-value multiplier, reduces the income-to-expenditure pass-through across the distribution, with only a partial rebound in 2022. Second, income-stabilisation policies implemented during the pandemic are consistent with this broad-based compression of EIEs; however, the EIE profile remains downward-sloping across quintiles and the recovery is incomplete at the lower end of the distribution.[26]

2.9 Fiscal Policy Scenarios

In this paragraph, we explore the relevance of the EIE heterogeneity for evaluating the effects of income changes on aggregate economy. In particular, we show how the estimates presented in the previous sections can be used to work out the effects on aggregate consumption of a series of fiscal interventions. In evaluating the effects on consumption of these fiscal

[26]The estimated σ's in Table 2.10 are structural standard deviations of the idiosyncratic income components implied by our calibration; they are chosen to match the empirical EIE profile and should not be read as statistical measures of uncertainty (e.g., standard errors of the estimates) nor as comprehensive indicators of aggregate or macroeconomic uncertainty. In particular, they pertain to individual-level shocks after conditioning on observed EIEs, and thus exclude economy-wide disturbances. Parameter uncertainty is instead quantified by the confidence sets reported for the calibrated parameters (via the bootstrap over target moments).

experiments, we use the estimated EIE distribution from our results (which control for a large set of variables) related to the decile or, alternatively, quintile regression.

It is important to note that the findings shown below are illustrative and should be interpreted in terms of how redistributive policies or policies aimed at those in need may effect aggregate consumption, rather than at face value. Specifically, we consider several experiments where we assume the government implements a transfer policy financed by debt (no taxes are imposed).[27] To do it, we make use of the EIE distribution estimates to calculate the potential response to a hypothetical targeted public transfer of transitory type.

In particular, we study a case in which government transfers an amount equivalent to 1% percent of national disposable income.[28] It is assumed to be uniformly distributed among all individuals targeted and temporary (*una tantum*).

Specifically, we consider two sets of scenarios: in the first, the EIE estimate is the same for all individuals (the OLS estimation based on the average, see Table B1.1); in the other, the EIE is heterogeneous across the sample distribution (the decile regression, see Table 2.4). From these EIE estimates we are able to draw the implicit value of the propensity to spend ($\Delta C/\Delta Y$) in order to evaluate the impact of the transfer policy on the aggregate consumption growth.

Specifically, the analysis compares the effects from the policy interventions in the homogeneous model with the ones corresponding to decile regressions to capture differences in consumption behaviour. By comparing aggregate consumption responses under homogeneous and heterogeneous case, this analysis highlights how redistributive policies and targeted transfers might affect consumption behaviour differently. Among the heterogeneous models, we also attempt different targeting (to unemployed, foreign-born or fixed-term contract).

Table 2.11 reports the results of the experiments where we show the aggregate $\Delta C/\Delta Y$ elaborated on the EIE estimates and the relative consumption growth resulting from the experiments.

In the homogeneous case, the estimated variation of consumption as a result of the transfer policy to a tenth of the population, $\Delta C/\Delta Y$, is 0.19, and the corresponding consumption growth is 0.44%. However, if the transfer is targeted to the first decile of the population, the effects on consumption change dramatically. For the bottom income decile, the effect

[27]The funding source of the policy is beyond the scope of this illustration, but it could be easily introduced in a revenue-neutral or balanced-budget scheme with taxation on the households with lower elasticity (higher income brackets).

[28]Data is delivered by Istat official statistics in 2022.

Table 2.11: Effect of Fiscal Policy Experiment (Transfers to Households)

Policy targets	**Model**	$\Delta C/\Delta Y$	**Growth (C)**
Homogeneous			
Representative agent	OLS	0.19	0.44%
Heterogeneous			
I decile	Decile (QR)	0.38	0.86%
Unemployed		0.29	0.67%
Foreign-born	Quintile (QR)	0.19	0.43%
Fixed-term contract		0.24	0.55%

Notes: Estimation of aggregate consumption growth out of a hypothetical monetary transfer of 1% of national income equally distributed among all individuals in the bottom 10 percent of the income distribution and temporary, targeted to different households (first column). *Model* indicates where the estimates come from, i.e. the coefficients used for the fiscal policy experiment. In Quintile regressions, targets belong to the first quintile.

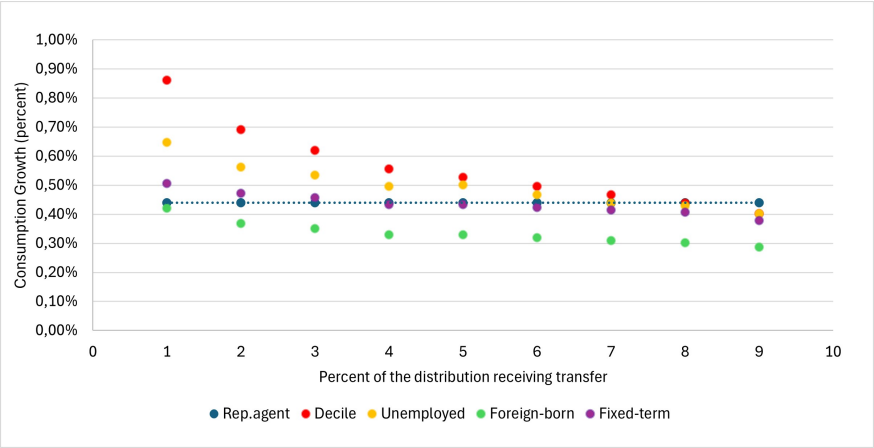
on consumption more than doubles to 0.38, with an aggregate consumption growth reaching 0.86%. This result is in line with such a similar exercise obtained by Jappelli and Pistaferri (2014). Furthermore, the difference between homogeneous and heterogeneous models show that the distribution of the population is crucial to shape an effective policy.

A different type of implementation regards the targeting of specific categories, for which we use the Quintile regression estimations (see Appendix B1). In this case, the heterogeneity concerns socioeconomic aspects like labour status, citizenship and contract type. The results observed among the unemployed are remarkable, with the highest multiplier of $\Delta C/\Delta Y = 0.29$, and a relative consumption growth of 0.67%. These results highlight the disproportionate impact fiscal transfer measures can have on low-income households, consistent with the findings highlighted in Section 2.6.

Foreign-born households exhibit a lower $\Delta C/\Delta Y = 0.19$ compared to the bottom income decile or unemployed, with a lower growth in consumption (0.43%). This outcome may reflect differences in savings behaviour or remittance obligations, as suggested by prior literature (see Table 2.4). Similar results are shown also by households with a fixed-term contract in the first quintile, with a multiplier of 0.24 and a corresponding consumption growth of 0.55%.

Figure 2.1 displays the aggregate consumption growth yielded by the policy targeted to different deciles and to specific categories. The heterogeneity in income distribution and individual characteristics is key to evaluating the effects of the transfer relative to the representative agent impact (horizontal line). Indeed, while the representative-agent impact

Figure 2.1: The Effects of Redistributive Transfer Programmes



Notes: Figure representing the aggregate consumption growth after different policy targeting. The transfer is equally simulated for all deciles (heterogeneous), while the horizontal line indicates the representative agent (homogeneous case). The cost of the policy is constant throughout all the experiments.

is constant throughout the distribution (by construction), the corresponding heterogeneous consumption growth declines over deciles as expected, due to the higher estimated elasticity of agents, being highest if the fiscal intervention is targeted to those in low-income groups (see Table 2.11). One might wonder how much of these aggregate consumption effects are due to a correlation between the expenditure and the income distributions as opposed to conditional factors of the quintile regression (basically, socioeconomic factors). To control for these confounding factors, we run the baseline regression without the socioeconomic variables to compute the consumption effect that can be attributed to the heterogeneity across expenditure and income, without controlling for demographic characteristics. Our analysis suggests that income heterogeneity accounts for around 50 percent of aggregate consumption growth, with the other 50 percent attributed to other conditioning variables. For example, consider the above redistributive strategy aimed at the bottom 10 percent of the population. The results indicate that aggregate consumption will rise by 0.86 percent (see Table 2.11). In this case, the rise that can be attributable to pure variability in the income distribution is 0.44% while the heterogeneity from non-income sources is estimated to be 0.42%.

2.10 Robustness Analysis

To ensure the reliability and generality of our findings, we carried out several robustness checks concerning different units of observation, methodological approaches, model specifications, and sample selections.

In the first place, we conduct an equivalent analysis at household level to test the implications of using single individuals as the unit of observation. Moreover, we present an unconditional quantile regression to compare it with the methodology used in the previous sections (for both these points see Section 2.10.1). Then, we extend the model, including proxies of wealth and home-ownership, or a quadratic term (see Section 2.10.2). Finally, we use different sample selections, excluding retired, minor, or self-employed people, and another definition of expenditure without imputed rents (see Section 2.10.3). We have consistently employed bootstrapped standard errors to address sampling variability and confirm the statistical significance of our results.

2.10.1 Household-level Analysis and Unconditional Quantile Regression

While in the previous section the analysis has been carried out at individual level to ensure the largest characterisation of agents, we run such a similar regression at the household level. Specifically, in a separate quantile regression, whose results are reported in Table 2.12, we use household definition of expenditure and income, equivalenced by *OECD-modified scale*.[29] These estimates allow for a comparison with the individual level, despite the lower amount of possible control variables granted by the larger scale of unit.[30] The results show that the shape of the curve, from the bottom to the top quintiles, is similar to individual-level case. Nonetheless, the overall magnitude of elasticities is higher, ranging from $logY = 0.233$ ($SE = 0.007$) in the first quintile to 0.182 ($SE = 0.007$) at $q80$. The structure of a household unit, normally larger than one individual, explains thus the difference with the corresponding individual-level case as in Table B1.2.

Additionally, we re-estimated the EIE using alternative quantile regression techniques to capture potential estimator-related bias using an unconditional quantile regression. The

[29]The scale assigns 1 to the household head, 0.5 for each additional adult and 0.3 for each child.

[30]In this case the analysis has been conducted at the family level. This is why the regression cannot incorporate individual characteristics.

Table 2.12: Household equivalenced consumption and income (OECD-modified scale)

Variable	**q20**	**q40**	**q60**	**q80**
$log(Y_{eq})$	0.233***	0.216***	0.205***	0.182***
	(0.007)	(0.005)	(0.006)	(0.007)
Married	0.010	0.019**	0.006	-0.012
	(0.009)	(0.009)	(0.008)	(0.012)
Urban	0.122***	0.111***	0.106***	0.104***
	(0.008)	(0.007)	(0.007)	(0.009)
North	0.037***	0.041***	0.044***	0.040***
	(0.009)	(0.007)	(0.007)	(0.011)
South	-0.235***	-0.218***	-0.195***	-0.170***
	(0.009)	(0.009)	(0.010)	(0.012)
Tenants (rent)	-0.193***	-0.191***	-0.197***	-0.219***
	(0.015)	(0.015)	(0.014)	(0.020)
Home-ownership	0.054***	0.063***	0.069***	0.062***
	(0.013)	(0.011)	(0.013)	(0.017)
Family size	-0.058***	-0.059***	-0.057***	-0.062***
	(0.003)	(0.003)	(0.003)	(0.005)
constant	7.257***	7.655***	7.967***	8.494***
	(0.071)	(0.055)	(0.057)	(0.069)
Pseudo-R^2	0.167	0.154	0.139	0.120

Notes: Estimation performed at household level, using a conditional quantile regression with 500 bootstrap replications. Thus, only familiar variables included (area of residence), and household values are scaled by the *OECD-modified equivalence scale*. Standard errors are reported in parentheses. The dependent variable is $log(C_{eq})$ and the quantiles are 5 (quintile). The interquantile differences of $log(Y_{eq})$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 60,225.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

results of these further estimates are confined to Appendix B3 (see Table B3.3), while the Figure B1.2 displays the EIE curve showing that the key features highlighted in the previous Sections still hold.

2.10.2 Model Extensions

We tested the sensitivity of the Expenditure-Income Elasticity (EIE) estimates to alternative specifications of the *Engel Curves* model, with the inclusion of measures of liquid (moveable assets) and illiquid wealth (fixed assets) as regressors[31], and a dummy for home-ownership. Estimation results including those further variables are reported in Appendix B3. While

[31]These variables come from the ISEE declaration, which thus not cover the full sample.

the general pattern of declining EIE across income quantiles is consistent with the benchmark formulation as in Table 2.4, the magnitude of the coefficients is slightly attenuated, as shown in Table B3.1. However, augmenting the specification with measures of liquid wealth (movable assets) and illiquid wealth (fixed assets) sharpens the picture of heterogeneity in expenditure behaviour. Across the income distribution, the coefficients on both asset measures are positive and comparatively stable, implying that households with larger asset holdings display systematically higher expenditure levels conditional on income and covariates. Together with the slight attenuation of the income elasticity relative to the benchmark, this pattern is consistent with wealth operating as a proxy for permanent resources: asset–rich households depend less on contemporaneous (transitory) income to adjust spending and can smooth consumption more effectively.

Turning to an alternative model specifications, we use home-ownership as a proxy for housing wealth yielding a positive association with expenditure only when imputed rents are included in the expenditure definition, in a way highlighting the specific role of housing services in the budget constraint. Specifically, following Cho et al. (2024), we use the home-ownership as a proxy for fixed assets. The results are reported in Table B3.2, where we show that the estimated EIEs are quantitatively similar to the previous case. In particular, the positive association between home-ownership and expenditures highlights the role of housing wealth in moderating consumption behaviour.[32] The role of moveable assets is stable, while the shape of elasticity curve is again declining from the bottom to the top quantiles.

It is worth noticing that, while we use wealth just as a control variable, a complementary strand of the literature models consumption directly as a function of household wealth — either alongside or in place of income — to capture permanent-income and collateral/liquidity channels. For instance, Campbell and Cocco (2007) studied the trend of British retail prices, highlighting a direct price effect and the heterogeneity of the wealth effect (permanent income). Mian et al. (2013) analysed, from a different perspective, the effect of negative wealth shocks on consumption, such as the retail prices fall during the Great Recession. The estimated consumption-wealth elasticity reveals a strong wealth effect, similar to a permanent income effect, and the impact was stronger for low-income or indebted households. Kaplan et al. (2020) confirmed those results using similar data and different approaches. Consistently, Carroll et al. (2017) highlighted that wealth distribution is a key determinant of policy effectiveness. J. D. Fisher et al. (2020), focusing on the synergy among income, con-

[32] In a separate regression we use a different definition of expenditures (see Table B3.8).

sumption, and wealth inequality in defining the life-cycle budget constraint, show that the marginal propensity of consumption is relatively low at higher wealth quintiles and higher for low-wealth households.

Finally, another possible alternative is the quadratic specification in log total outlays proposed by Banks et al. (1997). In the single-composite-good case used here, this implies a parsimonious quadratic-in-log Engel curve that captures curvature in responses to resources. This extends the previous system by allowing greater flexibility of Engel curves, with the same assumptions and improved empirical fit. Table B3.4 reports the estimates of the regression including a quadratic term of log-income, which underlines some non-linearities. In this context the coefficients are negative due to the presence of the quadratic term, which conversely exhibits positive coefficients, and the derivation process ultimately returns consistent results with Table 2.4. However, although the EIE estimation is not directly computable, the general trend of $log(Y)$ holds throughout the distribution, decreasing from -0.458 (0.031) at $q10$ to -0.724 (0.054) at $q90$.

2.10.3 Alternative sample selections and expenditure definition

In this section we analyse the stability of EIE estimates across sub-samples of the data, such as stratification by income sources, age and geographical location. The results are reported in Appendix B2 for the geographical location and Appendix B3 for income sources and age. The location of residence plays a role, with various effects due to the weather or cultural habits, according to the macro-region or the home-town size (urban or rural). The general trend of elasticity is declining overall for all the selected subsamples.

Table B3.5 excludes retired individuals, which marginally increases the EIE estimates across quintiles compared to Table B1.2. This is likely because retired individuals tend to have lower EIEs due to stable pension incomes, which dampens aggregate sensitivity. Table B3.6 excludes individuals under 18. The EIE estimates are slightly higher in some quintiles compared to Table B1.2, as young individuals typically contribute less directly to consumption decisions. This also might explain why the rate of decline in EIE across quintiles is steeper in Table B3.5 than in Table B3.6, suggesting that retired individuals exert a stabilising effect on consumption responsiveness as their exclusion increases variability in other groups. Furthermore, the impact of unemployment is notably lower in Table B3.5, likely because the exclusion of retired individuals shifts the sample composition towards

active workforce groups, diluting the unemployment effect observed in Table B1.2.

In Table B3.7 we excluded self-employed workers, a large portion of Italian labour force, since their income source is relatively more uncertain than the contract of employed workers. Interestingly, estimates are slightly different, since the curve is flatter and not linear - strongly declining only at the highest quintile. This non-linear pattern might be explained by the stronger income non-linearity among self-employed workers relative to employed people.

Moreover, we assessed the stability of EIE estimates adopting different assumptions about the expenditure definition. Specifically, in Table B3.8, are reported estimation results using a different definition of expenditure. Specifically, we exclude imputed rents from the expenditure definition.[33] The EIE values in Table B3.8 are slightly higher across all income quintiles compared to benchmark estimates as in Table 2.4. Indeed, the exclusion of imputed rents reduces the expenditure base, especially for wealthier households who benefit more from housing equity. This adjustment results in relatively higher EIE estimates, particularly in the lower and middle income quintiles, where housing wealth is less pronounced. However, while the overall patterns remain consistent with the benchmark, the shifts in magnitude highlight the moderate role of housing wealth in reducing consumption responses across different income groups.

2.11 Conclusions

This study has explored the heterogeneity in the Expenditure-Income Elasticity (EIE) among Italian households, emphasising the variability across income levels, demographic characteristics, and categories of expenditure. By employing a quasi-panel dataset and using quantile regressions, we provide some estimates of how disposable income changes affect household expenditure decisions. Our findings highlight some key points. The analysis reveals that EIE decreases as income rises, with lower-income households showing significantly higher consumption responses to income changes. This result is consistent with theories of liquidity constraints and highlights the importance of income distribution in shaping aggregate consumption behaviour. Variables such as employment status, geographic location, family size, and age emerged as significant determinants of EIE heterogeneity. Notably, unemployed individuals and younger households exhibit higher EIEs, while retired households

[33]Imputed rents are figurative values of a hypothetical rent for the dwellings, in the case of home-ownership. They are normally included in the line of *Utilities & Housing* to make the expenditure comparable with the people who pays an actual rent.

show lower responsiveness due to stable income streams from pensions. Furthermore, the study highlights significant variations in EIE across expenditure types. Durable goods, often requiring lump-sum investments, show higher EIEs, especially among lower-income households. Conversely, non-durable goods and essential services display more stable but lower EIEs, reflecting their necessity in household budgets. Moreover, external shocks, such as the COVID-19 pandemic and the Russia-Ukraine war, significantly influenced EIE across income groups. These events led to increased precautionary savings and reduced EIE, particularly among middle- and lower-income households, reflecting heightened economic uncertainty and constrained spending opportunities.

In this context, we show that a simple heterogeneous-agent buffer-stock framework à la Aiyagari (1994), together with pandemic income-stabilization policies, rationalizes the observed compression of expenditure–income elasticities as the persistence and volatility of near-permanent income shocks declined, in a way flattening (but not reversing) the downward-sloping profile and leaving the recovery incomplete at the lower end.

These results have important policy implications. The strong heterogeneity in expenditure responses suggests that uniform fiscal measures may have uneven effects across the population. Policies aimed at stimulating consumption, such as income support programmes or targeted tax reductions, should consider the distributional impact across different income strata. Additionally, the regional disparities in consumption responses highlight the need for geographically differentiated policy interventions, particularly in Southern Italy, where households exhibit lower elasticities and potentially higher constraints. Furthermore, the temporal analysis highlights structural changes in consumption patterns induced by fiscal policies like the *Reddito di Cittadinanza* and the stabilising effects of post-pandemic economic recovery. These shifts underline the effectiveness of targeted income transfers in mitigating the consumption disparities caused by income shocks.

By emphasising the importance of heterogeneity in EIE, this paper provides key insights for policymakers, highlighting the necessity of tailored fiscal interventions to mitigate economic inequality, support vulnerable brackets of the population, and stimulate aggregate demand during downturns. From a fiscal policy perspective, the results suggest the importance of accounting for the heterogeneous consumption response to income changes. In particular, redistributive interventions targeted at lower-income groups are likely to generate stronger multiplier effects on aggregate demand, while simultaneously contributing to the reduction of inequality. The quantile-based estimation of the Expenditure-Income Elasticity

(EIE) offers a useful tool for calibrating fiscal measures — such as cash transfers, bonuses, or tax reliefs — in a more effective and targeted way, especially in contexts of macroeconomic shocks or energy crises. The observed heterogeneity thus reinforces the idea that a *one-size-fits-all* policy is inefficient in promoting an optimal consumption response. Future research could extend this analysis by incorporating longitudinal dynamics, wealth effects, or cross-country comparisons to further refine our understanding of consumption behaviour.

Chapter 3

The Multidimensional Welfare Effects of Italy's Minimum Income (RdC)

Abstract

This paper provides a comprehensive evaluation of the multidimensional welfare effects of Italy's Citizenship Income (Reddito di Cittadinanza, RdC), analysing its impact on consumption- and income-based poverty, household expenditure and labour market. Using rich microdata from the AD-HBS dataset, we apply a difference-in-differences approach combined with propensity score matching, and difference-in-discontinuity design as complement analysis. The results indicate that RdC significantly reduced both income-based and consumption-based poverty, lowering relative poverty by 5 percentage points and absolute poverty by 4 points among recipients. The programme also increased household consumption by approximately 4%, suggesting meaningful improvements in material living standards and providing evidence of its role as an automatic stabiliser during economic downturns. However, we also document a modest increase in unemployment and inactivity, along with a mild reduction in employment share, suggesting possible disincentives to formal labour participation.

Keywords: Minimum Income Scheme, Public Policy Evaluation, Consumption, Diff-in-diff.
JEL classification: D6, H2, I3.

3.1 Introduction

The success of Minimum Income Schemes (MIS) in protecting vulnerable groups has taken central stage in the recent public policy debates, especially in the context of rising economic inequalities, labour market volatility, and repeated macroeconomic shocks, that have been particularly daunting for low-income households. Designed as last-resort safety nets and automatic stabilisers, MIS aim not only at lifting households above the poverty line but also to sustain consumption and mitigate material deprivation during downturns (Immervoll et al. (2007); OECD (2013)). Beyond their impact on disposable income, theory and evidence suggest that transfers can ease liquidity constraints, smooth expenditure over time, and support access to essential goods and services, generating broader social returns in health, education, and social cohesion, as widely documented in Atkinson (1995), and Figari et al. (2013). The COVID-19 crisis has made these functions particularly salient, exacerbating the vulnerability of low-income households and the limits of incomplete safety nets.

In this regard, Italy offers an important case study. Between 2008 and 2018 absolute poverty among individuals in Italy more than doubled, rising from 3.6% to 8.4% (and from 4% to 7% among households), while among minors it soared from 3.7% to 12.6%. The relative poverty followed a similar path, from 11.1% to 15% among individuals (and from 9.9% to 11.8% among households). During the same period, the share of people at risk of income poverty increased from 18.9% to 20.3%, people not able to cover unforeseen expenses rose from 32.5% to 36.4%, and also inequality incremented, with Gini index going from 0.294 to 0.303 (0.324 to 0.335 according to different definitions).[1]

In response to these alarming trends and to align with EU recommendations on social inclusion, the Reddito di Cittadinanza[2] (RdC) was introduced in 2019 as a means-tested programme combining income support with activation aims. Despite the "citizenship income" label, the RdC is not universal: benefits are calibrated by household composition and housing status, with strict income/wealth tests and residency conditions. See Section 3.3 for more details, where Table 3.1 provides information about the binding legal requirements. This design, generous relative to prior schemes but tightly targeted, sparked the

[1] All the data here reported is obtained from ISTAT, under the category *Households economic conditions and disparities*.

[2] The RdC is no longer in force. Decree–Law No.48 of 4 May 2023 ("Decreto Lavoro"), converted by Law No.85 of 3 July 2023, abolished the programme and introduced two new instruments: the Inclusion Allowance (*Assegno di Inclusione*, ADI) effective from 1 January 2024, and the Support for Training and Work (*Supporto per la Formazione e il Lavoro*, SFL) effective from 1 September 2023. See the *Gazzetta Ufficiale* for the legal texts (D.l.48/2023 and L.85/2023) and INPS guidance on ADI and SFL.

debate about distributive gains, labour-supply incentives, and the degree to which transfers stabilise consumption through business cycle phases.

Unlike most existing studies focusing narrowly on income poverty and inequality (Curci et al., 2020; Gallo & Raitano, 2019; Maranzano et al., 2025) or labour market effects (Aprea et al., 2024; Busilacchi & Fabbri, 2024; Carta & Colonna, 2025; Maitino et al., 2024), this paper contributes to the literature on MIS by providing a comprehensive assessment of the Italian Citizenship Income (RdC) along three key dimensions - poverty, labour, and household expenditure - so delivering an integrated view of welfare impact. Specifically, the latter dimension represents a novelty in the literature, which focuses on the material living standard of recipients, proxied by household aggregate consumption. Moreover, the use of consumption-based poverty measures, which directly capture households' ability to meet material needs, is still relatively limited in the Italian context. In this sense the analysis highlights important implications for the broader debate about poverty reduction policies, social safety nets, and their possible trade-offs with employment incentives. The paper offers a richer, multidimensional perspective on how such measure affects material living standards and the functioning of the labour market.[3]

Our analysis exploits AD-HBS, as further explained in Section 3.4, a rich dataset linking Italy's Household Budget Survey and INPS administrative record, covering 2017–2023, i.e., pre-introduction, roll-out, and the Covid/post-Covid years. As a result, it allows for robust causal inference not only on the immediate impacts of the RdC but also on its evolution over time, capturing adjustments during economic shocks, such as Covid-19 and the inflation spike in 2022. The timeframe is relevant, since it covers tumultuous years where the introduction of minimum income could have been crucial for many households to face daily expenses. Identification relies on difference-in-differences with propensity score matching, complemented by a difference-in-discontinuity design around eligibility thresholds, allowing us to isolate the causal effect of receipt while addressing selection and composition concerns. The study is conducted at household-level, according to the scheme design.

The analysis shows that the RdC significantly reduced relative poverty by 5 percentage points and absolute consumption-based poverty by 4 points among beneficiaries, indicating

[3]Some other contributions focus on different aspects of the RdC. Giuliani (2024) explored the political effects of RdC on electoral results of parties, while Nesti and Graziano (2025) instead analysed the policy legacies behind the implementation mechanisms. Checchi et al. (2021) addressed the issue of the unequal geographical distribution of beneficiaries. Interestingly, Dachille et al. (2025) found that, using an RDD approach on fertility, the occurred economic stability yielded to an increase in childbearing in the South.

meaningful improvements in material living standards. At the same time, the programme increased aggregate household consumption by approximately 4% compared to comparable non-recipients, suggesting an important role in sustaining demand, especially during the economic disruptions of the Covid-19 years. However, the study also finds evidence of a modest rise in unemployment share by about 6 percentage points among recipients, raising concerns over potential disincentives to formal labour market participation. Consistently, we found a modest decrease in employment share. These findings highlight the challenging trade-offs inherent in minimum income schemes, pointing out both their effectiveness in reducing poverty and supporting consumption, but also the challenges in maintaining work incentives.

The remainder of the paper is structured as follows. Section 3.2 provides an overview of the related strands of literature. Section 3.3 describes the legislative framework of the RdC. Section 3.4 presents the data and Section 3.5 the methodology. Section 3.6 reports the main results, while Section 3.7 concludes.

3.2 Main relevant related literature

Minimum income schemes (MIS) and closely related income support programmes constitute the core non-contributory component of social protection and have been extensively examined in the international literature. Existing studies have been developed along three main dimensions: their effectiveness in reducing poverty and smoothing consumption, their labour supply and employment effects, and their role as automatic stabilisers during downturns. However, despite the volume of empirical work, the evidence remains disjointed and difficult to generalise across contexts: programme designs differ substantially across countries, evaluation strategies are heterogeneous, and outcomes are often measured inconsistently (Cantò et al., 2022; Pacifico et al., 2018). Moreover, most contributions typically focus on a single welfare dimension rather than on integrated, multidimensional perspective.

A first strand of research examines the effectiveness of MIS and guaranteed minimum income (GMI) programmes in reducing poverty and mitigating material deprivation. Initial work framed MIS primarily as last-resort safety nets (Marx & Nelson, 2013). Subsequent research broadened this view by highlighting concerns around welfare dependency (i.e., the possibility that long-term reliance on income support may reduce incentives to seek employment) and the risk of poverty traps, whereby high effective marginal tax rates for beneficiaries

make transitions into low-paid jobs financially unattractive (Immervoll & Pearson, 2009). More recent work has examined how MIS have evolved within contemporary welfare states, balancing income protection with activation requirements and labour-market participation goals (Natili, 2020). Over time, MIS have evolved towards activation-oriented and workfare-based designs (Groot et al., 2019; Hemerijck, 2017; Spies-Butcher, 2020; Xu & Carraro, 2017), though substantial cross-country heterogeneity remains in generosity, conditionality, and administrative capacity. Empirical evaluations generally document meaningful reductions in poverty incidence and depth, with evidence from Spain showing substantial declines in the intensity and severity of poverty among beneficiaries (De La Rica & Gorjón, 2019; Rodrigues, 2001), and recent analyses highlighting the stabilising role of income support during the COVID-19 shock (Brewer & Tasseva, 2021; Cantò et al., 2022; Figari et al., 2020). In Italy, existing studies similarly find that the Reddito di Cittadinanza (RdC) contributed to lower poverty and inequality (Baldini et al., 2019; Gallo, 2021; Tonutti et al., 2022), though evidence has remained fragmented and focused on individual margins.

A second major strand of literature investigates labour supply responses to MIS and the potential employment disincentives generated by means-tested transfers. Standard labour supply models predict that guaranteed income raises reservation wages and may reduce participation, particularly among individuals with high labour supply elasticity (Meghir & Phillips, 2010; Moffitt, 1992). Empirical findings, however, are more nuanced. In France, the *Revenu minimum d'insertion* (RMI) has been shown to reduce labour force participation among uneducated young men (Bargain & Doorley, 2011) and to delay exits from unemployment, especially during the early months of receipt (Terracol, 2009), though effects largely disappear for other demographic groups (Simonnet & Danzin, 2014). Evidence from Spain and Germany also indicates limited or short-lived negative effects on job-finding rates or activation outcomes (De La Rica & Gorjón, 2019; Hohmeyer & Wolff, 2007; Wolff & Nivorozhkin, 2012), while Scandinavian studies show that programme impacts vary significantly by age, pre-programme attachment, and activation intensity (Heinesen et al., 2013; Rønsen & Skarðhamar, 2009). In Italy, the labour market effects of the RdC remain contested. The most rigorous causal evidence available to date shows limited or null aggregate disincentive effects (Busilacchi & Fabbri, 2024). Their province-level difference-in-differences analysis reveals that areas with higher concentrations of beneficiaries did not experience systematically different employment trajectories after implementation relative to other areas. However, they identify non-negligible territorial heterogeneity: in provinces with weak la-

bour demand and low institutional capacity, the programme appears to generate modest negative employment effects, consistent with behavioural responses shaped by local labour market constraints rather than by the design of the transfer itself. Structural models for Italy indicate that minimum income schemes can create household-level labour supply complementarities, especially among single-earner couples. Because eligibility depends on total household income, partners may jointly choose non-employment to retain the benefit. Carta and Colonna (2025) find that the citizenship income mainly reduces employment among married men with non-working wives, with limited effects on women and singles. Ex-post administrative evaluations, however, detect only modest or insignificant employment declines, suggesting that these theoretical disincentives translate weakly into actual behaviour. Further evidence finds that activation services[4] attached to the RdC neither substantially reduced employment nor generated significant improvements in labour market transitions (Maitino et al., 2024), in line with broader studies emphasising the importance of job-search incentives, monitoring and institutional quality in shaping beneficiary behaviour (Gangl, 2006; Schmieder & Von Wachter, 2016). Overall, this evidence points to labour supply responses that are more nuanced than public debates suggest. While some subgroups may adjust their employment behaviour in the presence of income support, these effects are neither large nor systematic and fall far short of the *unemployment trap* narrative. Any labour market responses must therefore be weighed against the sizeable improvements in income security, poverty reduction, and consumption smoothing documented in the literature, which typically represent the primary policy objectives of minimum income scheme.

A third strand of research underscores the territorial and institutional dimensions of minimum income schemes, showing that their effectiveness depends not only on benefit design but also on the socioeconomic and administrative contexts in which beneficiaries are situated. MIS take-up, targeting accuracy and coverage are known to vary significantly across the territory, reflecting local disparities in income distribution, poverty incidence, governance quality and social capital (Albanese et al., 2023; Bargain et al., 2012; Bhargava & Manoli, 2015; Checchi & Peragine, 2010; Felice, 2018; Lagravinese, 2015). In Italy, the citizenship income (Reddito di Cittadinanza - RdC) provides a clear example of such spatial disparities. The incidence of RdC receipt - the proportion of households receiving the benefit - varies

[4]Activation services refer to the set of job-search assistance, training programmes, monitoring requirements and supportive measures delivered by public employment services with the aim of facilitating beneficiaries' labour market integration. These activities are typically linked to conditionality rules and are intended to counteract potential work disincentives associated with income support.

markedly across regions, with substantially higher concentration in Southern areas. Maranzano et al. (2025) document the geography of the citizenship income, showing strong spatial heterogeneity in take-up and spending: the programme is more heavily used in Southern regions and in areas with high pre-existing poverty and weak labour demand, but also reflects administrative capacity and political factors. This raises concerns about unequal protection across space and suggests that the local labour market context is crucial for interpreting both welfare and employment effects. Italy's longstanding territorial divides (Cerqua & Pellegrini, 2018; Mussida & Parisi, 2020) reinforce these patterns, potentially attenuating the uniformity of MIS outcomes and complicating comparisons based solely on national aggregates. This literature suggests that MIS effectiveness is deeply intertwined with local labour market opportunities and administrative capacity and therefore cannot be evaluated adequately without considering the territorial dimension. Institutional capacity further shapes these territorial disparities. Evidence from regional evaluations, such as Maitino et al. (2024) highlights weaknesses in the coordination and effectiveness of public employment services in the Tuscany region: coordination challenges among the various institutions involved in delivering the RdC - most notably the national social security agency, the public employment service, municipal welfare offices, and the temporary cohort of employment counsellors - have constrained the programme's activation dimension, limiting the effective implementation of job-search support and labour market integration measures. As a result, the labour market effects of the programme have been modest, with limited improvements in employment outcomes for job-seekers enrolled in activation pathways. These findings are consistent with broader European evidence showing that minimum income schemes tend to perform better when embedded within robust activation frameworks and well-functioning employment services; where institutional capacity is weaker, income support tends to function more as passive welfare than as an instrument of labour market integration (Card et al., 2018).

Taken together, the existing literature highlights that the design and performance of minimum income schemes cannot be assessed in isolation from their institutional and territorial environments, nor from their interaction with labour market dynamics and household behaviour. The Italian case - marked by pronounced regional disparities, evolving activation infrastructures, and a MIS reform that recently shifted towards more restrictive categorical criteria - provides a particularly salient setting for reassessing the core policy functions of income support. The multidimensional perspective adopted in this paper directly speaks to ongoing policy debates, both in Italy and in Europe, concerning the balance between

poverty alleviation, work incentives, and the stabilising role of transfers during economic downturns. By documenting how the RdC simultaneously affected poverty, consumption, and unemployment, our findings offer evidence that can inform future reforms aimed at reconciling income protection with effective activation, while recognising that the success of such schemes ultimately depends on the broader institutional capacities and local labour market opportunities in which beneficiaries are embedded.

3.3 The Minimum Income Scheme in Italy: the implementation of the Citizenship Income

The introduction of the *Reddito di Inclusione* (REI) in 2018 and, shortly thereafter, the *Reddito di Cittadinanza* (RdC) in 2019 marked a major breakthrough in Italian anti-poverty policy, following years of limited interventions and more than fifteen years after the first pilot of a minimum income scheme (*Reddito Minimo di Inserimento*, RMI). The legislative decree that established the RdC defined it simultaneously as an "active labour market policy" and as a measure to "combat poverty, inequality, and social exclusion". This dual rationale reflects a broader European trend: minimum income schemes have progressively evolved from residual, passive last-resort benefits into instruments designed to combine poverty alleviation with labour market activation (Marchal et al. (2018); Barbieri et al. (2018); Cantillon et al. (2020); Ciarini et al. (2023)).

Turning to the pratical application, the benefit was delivered monthly through an electronic card (*Carta RdC*) and is, in most cases, coupled with personalised pathways to employment or social inclusion. For recipients aged 67 years or older, the scheme takes the form of the *Pensione di Cittadinanza* (PdC). Eligibility was subject to a dual means test: an *Equivalent Economic Situation Indicator* (ISEE) threshold of €9,360 and a minimum income threshold of €6,000. Compared to previous schemes, these thresholds were significantly more generous (Jessoula et al., 2019). For single-person households, the income threshold represented nearly 80% of both the relative poverty line (as calculated by ISTAT in 2021) and the severe poverty threshold based on 40% of median equivalised disposable income in 2022.

According to administrative data from the National Institute of Social Insurance (INPS) by May 2022 - during the first 36 months of implementation - 2.2 million households (almost

9% of all Italian households), corresponding to 4.8 million individuals, had received at least one monthly payment of RdC or PdC (INPS 2022). Total expenditure amounted to €22.71 billion, with €7.14 billion spent in 2020 and €8.82 billion in 2021, approximately 0.5% of GDP (Sacchi et al., 2023).

The maximum annual benefit for a single-person household was set at €9,360 (€780 per month), well above the national relative poverty line. Additional supplements were granted for housing costs (€280 for tenants, €150 for homeowners with a mortgage), though these were not adjusted for household size. Importantly, neither benefit levels nor eligibility thresholds were indexed to inflation. Moreover, the equivalence scale applied to adjust thresholds for household size tended to disadvantage larger families with children - who are among the groups most exposed to poverty in Italy - while comparatively favouring single-person households (Saraceno et al. (2020); Sacchi et al. (2023)).

From 2021 onward, RdC recipients also became eligible for subsidies covering water, energy, and sanitation services, and the benefit could be combined with earnings from employment. In principle, this made the RdC function as an in-work benefit (Ciarini et al., 2022). In practice, however, the design might have generated strong disincentives to employment: earnings reduced the benefit at a rate of €0.80 per euro, and after the annual update of the ISEE declaration, the marginal effective tax rate rose to 100%.

Overall, RdC operated more as an anti-poverty instrument than as a tool for labour market activation. Its design often positioned it as a substitute for employment, yet its redistributive impact was significant. By targeting the poorest households and providing relatively generous transfers, the RdC contributed to a measurable reduction in both the incidence and intensity of monetary poverty, albeit with important limitations.

Table 3.1 summarises the key eligibility criteria for the Reddito di Cittadinanza (RdC), highlighting the programme's highly targeted and means-tested nature. Access to the benefit depends simultaneously on citizenship and long-term residence requirements, strict income and wealth thresholds, and several exclusion criteria related to asset ownership, voluntary job resignation, and criminal records. The income test is based on the so-called ISEE[5] indicator, while additional limits on household income, real estate, and movable financial assets ensure that the scheme reaches households with very limited economic resources. The inclusion

[5]ISEE (*Indicatore della Situazione Economica Equivalente*) is Italy's official means-testing index, combining household income, assets and an equivalence scale to capture the economic condition of the family unit. It is the central eligibility instrument for a wide range of social assistance programmes, including the Reddito di Cittadinanza.

Citizenship	Italian or EU citizenship, or a family member holding the right of residence, permanent residence, or EU long-term residence permit.
Residence	Resident in Italy for at least 10 years, the last 2 of which must be continuous and immediately prior to the application.
Income requirement (ISEE)	Valid ISEE below €9,360.
Income (Household)	Household income below €6,000/year, multiplied by the equivalence scale. Raised to €7,560 for Pensions and €9,360 if renting.
Fixed Assets (Real estate)	Real estate (excluding primary residence) in Italy or abroad not exceeding €30,000.
Moveable Assets (Financial)	$\leqslant$ €6,000, +€2,000 per member, +€1,000 per child, +€7,500 per disabled.
Durable goods	No owned vehicles registered in the 6 months prior, or over 1,600cc / 250cc in past 2 years. No owned pleasure boats (D.L.171/2005).
Voluntary resignation	No eligibility for those who resigned voluntarily in past 12 months (except just cause).
Criminal record	No precautionary measures or final convictions for listed crimes in the 10 years before.

Table 3.1: Eligibility Criteria of Reddito di Cittadinanza (RdC).

of restrictions on durable goods, such as vehicle ownership, and on recent labour market behaviour further underscores the programme's intention to prevent strategic eligibility and to channel support toward households facing genuine socioeconomic disadvantage. Overall, the table illustrates the significant administrative complexity of RdC eligibility, and the extensive controls embedded in the design, which differentiate the programme from more universal or less restrictive minimum income schemes found in other European countries.

3.4 Data

The AD-HBS is a representative sample of the Italian resident population, by reproducing the key characteristics of the socio-demographic distribution. It links survey data on consumption expenditures of the Household Budget Survey (HBS) provided by the *National Institute of Statistics* (ISTAT) with the administrative data (AD) from *National Social Security Institute* (INPS). It is a database of repeated cross-sections, and each wave of HBS is a separate sample with different individuals, but it keeps the same distribution across time. It covers seven consecutive years[6] from 2017 to 2023, and all the variables are scaled up to yearly values.

[6]The sample contains: 37,589 individuals (16,946 households) in 2017; 40,622 (18,342) in 2018; 41,080 (18,718) in 2019; 56,387 (25,668) in 2020; 61,600 (28,608) in 2021; 59,049 (28,416) in 2022; and 60,147 observations (28,180) in 2023.

A large set of socio-economic and demographic variables of households is available. Among them, the family size (number of components), the place of residence (city or countryside) and the regional area (macro-regions and further disaggregation), the housing status (rent or home-ownership), and the economic condition of the family, including the household income, the poverty status (absolute and relative) and the *Equivalent Economic Situation Indicator* ($ISEE$), which assesses the comprehensive financial situation of a family. The ISEE results from the sum of the household income indicator (ISR) and the household wealth indicator (ISP), in turn formed by the evaluation of mobile and fixed assets[7]. The total expenditures are at household level, and they sum up the canonical consumption categories of goods and services of ISTAT[8].

Moreover, many individual variables about the family members are available; some of them are also used to build household-level indicators indicators, such as the age, the education level and the working status (e.g. unemployment or retirement).

The administrative data tracks information on labour earnings, pensions, and transfers (subsidies) allowing for differentiation of income sources as well as working status and employment contract. Among the various types of transfers, there are child benefits and public family allowances (ANF), minimum income transfers like *Inclusion Income* (ReI) in 2018 and *Citizenship Income* (RdC) from 2019, and other unemployment allowances[9]. For further details about the AD-HBS, see Aprea et al. (2023) and Aprea et al. (2024).

The sample population reflects distribution of the Italian population, as explained in the Section 3.4. Table 3.2 shows the number of beneficiaries in the sample. They are indicated as $Treated$. The measure was introduced in 2019 so that there are no receivers before that year. In the Table 3.2, two further columns are reported: $Not\ Treated$ refers to people who never received the subsidy and were not allowed to it, while $Eligible(NT)$ concerns the individuals who did not receive the transfer, but would have been eligible to. The latter groups is a first comparable control group. Looking at the total numbers, in the last row, they confirm that the take-up of the measure was around 60%, as officially exhibited by the institutional data

[7]Although the declaration is mandatory for most of the means-tested transfers, the rate of declaration is still below the 50% and subject to strong auto-selection of compilers. There are many reasons for this, ranging from the difficulty in dealing with bureaucracy to the fear of tax assessments, and/or the cost of doing it without any expected benefit.

[8]The disaggregation is limited to the nine main classes which are available for all the years: food and beverages, alcohol and tobacco, clothing, utilities and housing (including actual and imputed rents), furniture, health, private and public transport, media and telecommunications, and sport and culture (leisure).

[9]These latter benefits are disaggregated according to the working category (*NASpI, DIS-COLL*, and agricultural). In addition, the redundancy fund (CIG) records the salary compensation due to work suspension. The pensions are grouped as retirement, survival, disability, and others.

(Baldini et al., 2023). The take-up is the percentage of the actual beneficiaries out of the total eligibles in the target group.

Table 3.2: Distribution of individuals by year and treatment status.

Year	Not Treated	Eligible (NT)	Treated	Total
2017	35,576	2,013	0	37,589
2018	38,726	1,896	0	40,622
2019	37,900	856	2,324	41,080
2020	51,719	1,858	2,810	56,387
2021	57,168	1,425	3,007	61,600
2022	54,406	1,212	3,431	59,049
2023	54,682	2,833	2,632	60,147
Total	330,177	12,093	14,204	356,474

Notes: The table describes the distribution of individual per year, according to their status of treated, not treated but eligible, or not treated nor eligible.

Nonetheless, the minimum income scheme is mainly devoted to people belonging to the first quantiles of the income distribution, as elucidated in Section 3.3. Obviously, the distribution of the key socio-economic variables, such as the working status, home-ownership, and family size for instance, changes dramatically at different points of the distribution. Table 3.3 shows those differences: the columns $Not\ Treated$, $Eligible(NT)$ and $Treated$ report the percentage of the variables of interest, in their respective subgroups; the last column *Gap* highlights the relative difference between the treated group and the total population, in percentage terms.

There are few variables which have a similar share in both groups, such as the people living alone (*Single*, 17.8%), and the environment of the place of residence (*Urban*, 54.2%, and conversely *Rural*, 45.8%). All the other variables have a substantial difference of share, in terms of both percentage points or real percentage. The larger misalignment in the treated group concerns: the home-ownership, with a majority of $Tenants$ (55.6%) in a rental condition with respect to landlords (29%); the beneficiaries tend more to be part of a large family (17.5%), and not $Married$ (29.7%); a disproportionate representation of households living in the *South* (67%) with respect to *North* (17.7%); a relevant share of average unemployed people within households, $Unemployment(share)$ (26.7%); a higher presence of $Family\ with\ Children$ (50.1%) along with a lower share of $Retired\ Household$ (12.8%). All the above-mentioned variables suggest which could be the main drivers of economic fragility. Indeed, among the treated, 45% experiences a condition of relative poverty and 30% lives in

Table 3.3: Distribution of socio-demographic characteristics by treatment status.

Variable (%)	Not Treated	Eligible (NT)	Treated	Gap
Single	13.83	42.36	17.72	28.12%
Large Family (5+)	8.53	17.08	17.54	105.69%
Married	46.83	21.66	29.67	-36.63%
Retired Household	32.94	16.15	12.77	-61.23%
Family with Children	34.74	47.90	50.08	44.15%
Tenants (rent)	13.86	52.35	55.63	301.50%
Home-ownership	78.47	34.71	29.03	-63.00%
Urban	43.89	48.79	54.16	23.41%
Rural	56.11	51.21	45.84	-18.31%
North	45.30	29.76	17.73	-60.85%
Centre	22.15	20.27	15.26	-31.13%
South	32.55	49.97	67.01	105.86%
Low education	52.24	69.97	74.37	42.36%
High education	47.76	30.03	25.63	-46.34%
Relative Poverty	11.22	30.93	45.06	301.58%
Absolute Poverty	6.51	22.46	29.94	359.68%
Unemployment Share	5.81	14.25	26.73	359.61%
Average age*	47.40	44.20	38.75	-18.25%
Total	330,177	12,093	14,204	-

Notes: The values are intended as percentage. The *Gap* column computes the percentage difference between Treated and Not Treated.
**Average age* is the only variable not expressed as percentage, but in real values.

absolute poverty.

Moreover, education is correlated, since there is a disproportion of lower education levels (*LowEduc*, 74.4%) instead of higher ones (*HighEduc*, 25.6%)[10]. The age also matters: it is the only value expressed as real average (*Average age*, 38.8) and it suggests that younger people have a higher need of the subsidy than older ones[11].

It is crucial to know the composition of the groups, as reported from all the statistics in Table 3.3. With the aim of a policy evaluation, treated and control groups must be balanced in terms of relevant variables, otherwise there would be too many possible confounding factors. Controlling for as many dimensions as possible, we are ideally able to isolate the sole effect of the introduction of the subsidy, in order to discern between two identical groups except for the perception of the transfer. This balance is the key of the matching process explained in Section 3.5.

[10]This result is further aggregated into a standardised family indicator of average education level, *Education score*.

[11]This result is normalised at household level and scaled from 0 to 1 for sake of comparability.

3.5 Methodology

3.5.1 Matching Difference-in-Differences

There is a long tradition of empirical public policy evaluation and more recently methods for conducting causal inference in policy evaluation. The methodology used in this study concerns the application of a propensity score weighting in parametric Difference-in-Differences (DiD) models. The Propensity Score Matching (PSM) is a statistical technique that estimates causal treatment effects in observational studies. PSM was introduced by Rosenbaum and Rubin (1983) and entails the estimation of the conditional probability (*propensity score*) of receiving the treatment, given a collection of observed covariates. In this analysis, the matching variables are: outcomes (pre-trend), log-income, log-ISEE, rental status, family size, regional location. By default, PSM reduces the *selection bias* caused by those observed confounders and it enables the estimation of the Average Treatment effect on the Treated (ATT), as explained in Imbens (2004). The most common implementation is one-to-one pair matching, in which individuals in the treatment group are then matched to individuals in the control group who have similar propensity scores, resulting in a matched sample with a balanced distribution of variables between groups. In this analysis, the nearest-neighbour approach is applied (one-to-one and five-to-one).

The matching estimator assumes that, after conditioning on a set of observable features, the outcomes are independent of programme participation.[12] The conditional DiD matching estimator relaxes this requirement by accounting for unobservable but temporally invariant changes in outcomes between participants and nonparticipants. This is accomplished by comparing the conditional before-after mean outcomes of the participants with those of nonparticipants. It improves the traditional DiD estimator by defining outcomes based on the propensity score and using semi-parametric approaches to create the differences. It does not apply linear functional form constraints in estimating the conditional expectation of the outcome variable, and it reweighs the observations according to the weighting function of the matching estimator. The following identification assumption forms the basis of the DID propensity score matching estimator:

$$\mathbb{E}[Y_t(0) - Y_t'(0)|P(X), D = 1] = \mathbb{E}[Y_t(0) - Y_t'(0)|P(X), D = 0] \tag{3.1}$$

[12]The DID matching was originally introduced by Heckman et al. (1998).

where t is the post-treatment period, t' is the pre-treatment period, D shows the treatment status, and Y is the dependent variable of interest, conditioned to the probability $P(X)$, where X represents the covariates.

The matching weights are applied to reweight the sample such that the distribution of covariates becomes balanced across treatment groups, effectively simulating a randomized experiment. The resulting weighted sample allows for unbiased estimation of the Average Treatment Effect (ATE).[13]

PSM-DiD regression minimizes the following with respect to $(\alpha, \beta_1, \beta_2, \beta_3, \gamma_i)$:

$$\sum_{i,t} w_i \Big[\ln C_{it} - \big(\alpha + \beta_1 \, \mathrm{T}_t + \beta_2 \, \mathrm{Post}_i + \beta_3 \, \mathrm{T_t} \times \mathrm{Post}_i + \gamma_i \mathrm{X}_{it}\big) \Big]^2 \tag{3.2}$$

where w_i is the weight given to each observation, to reduce the selection bias and to balance treated and control samples, α is the constant term, T indicates the treated group (only eligibles before treatment), *Post* is the dummy for the post-treatment period and $T \times Post$ is the interaction term. The β_3 coefficient gives us the Average Treatment Effect on the Treated (ATT). Finally, X_i is a vector of control variables.

3.5.2 Parallel trend assumption and matching balance

The parallel trend assumption is normally tested graphically. In Appendix C1, the trends of treated and untreated is shown to be approximately parallel in the pre-treatment period (2017 and 2018). Figure C1.1 refers to the the matched subsamples.

Additionally, the goodness of matching is reported in Figure C1.2, which exhibits the density of all the outcomes. Moreover, all the covariates chosen for the matching process are now balanced, while before matching they were not. Figure C1.3 exhibits the results. Outcome variables (*Consumption*, *Poverty* and $Unemployment$) in the pre-treatment period are used for matching, along with variables which define the access to the subsidy ($Income$ and $ISEE$) and other main dimensions: *Rent*, $Large family$, *Children*, *Retired* and *South*.[14]

[13] There are four primary assumptions which must hold, reported in Appendix C1. For an extensive analysis of this technique, please refer to some specific studies on the subject, like Baker et al. (forthcoming), Roth et al. (2023), Greene and Liu (2020), Stuart et al. (2014), Lechner (2011) and Caliendo and Kopeinig (2008).

[14] The importance of these aspects reflects the distribution of the variables displayed in Section 3.4.

3.5.3 Difference-in-discontinuity

For completeness, we also consider the difference-in-discontinuity (Diff-in-disc), which combines the Diff-in-diff with the Regression Discontinuity Design (RDD). This latter approach is used when there is a clear threshold which regulates the access to treatment, as in our case. This method was developed by Grembi et al. (2016) and Eggers et al. (2018). The intuition is given by the following formula:

$$\hat{\tau}_{DD} \equiv \left(Y^- - Y^+\right) - \left(\tilde{Y}^- - \tilde{Y}^+\right).$$

where $\hat{\tau}$ is the diff-in-disc estimator, Y is the outcome variable of interest, $+$ and $-$ indicates the position with the respect to the threshold. This yields an estimation of the Local Average Treatment Effect (LATE). Indeed, this approach complements the previous analysis, since it regards the local effect on individuals who are similar to ones above the cutoff. While the diff-in-diff allows a general evaluation over the entire segment of beneficiaries, the diff-in-disc focuses on a more local (and homogeneous) population. This empirical methodology sheds light on where the treatment effects are concentrated.

In the case of Reddito di Cittadinanza, we have multiple thresholds, as reported in Section 3.3: the main one is with respect to the ISEE declaration and the income one is unfixed and dependent on the social conditions (rental status, retirement, disability).[15] The first one is fixed at €9,360 and the second oscillates from €6,000 (single with no rent) to €20,592 (in case of large family in a rental status, with a component in a disability condition), which is adopted as income threshold, in terms of logarithmic distance. In our case, the treatment is delivered below the selected thresholds, but in a *fuzzy* way. *Fuzzy* is derived from RDD literature and indicates when the treatment is not deterministic: the participation in the programme was indeed voluntary and the take-up rate did never reach 100%. The formal definition is given by:

$$Y_{it} = \alpha_0 + \beta_1 Post_i + \beta_2 Below_i + \beta_3 Post_i \times Below_i + \delta distance_i + \gamma_s \mathrm{X}_{it} + \epsilon_{it} \tag{3.3}$$

where $Post$ indicates the post-treatment period, $Below$ refers to the position with respect to thresholds, β_3 is the interaction coefficient of interest, $distance_i$ is the individual measure to

[15] The two thresholds about mobile and fixed assets, derived from ISEE declaration, are not used in this analysis.

control the distance from the thresholds, γ_i is the coefficient of a vector X of s explanatory variables, ϵ the error term; i refers to the individual and t to time.

In Appendix C2, there is additional material on Diff-in-disc. Notably, Figure C2.1 shows graphically the McCrary test on non-manipulation of thresholds before and after the treatment. The plots confirm absence of manipulation for both ISEE and income critical values. Instead, Figure C2.2 displays the discontinuity around the thresholds.

3.6 Results

In this section, the main results of the analysis are reported. Firstly, the coefficient of interest is the one of the variable $Treated\ x\ Post$. It indicates the actual behaviour of the treatment group, in the years of treatment, with respect to pre-treatment period and to control group. The variable *Eligible* is the trend of the eligible group with respect to the rest of population, while $Post - Treatment\ period$ is the general trend from 2019 to 2023 (years of implementation of the measure). This is valid for the interpretation of all difference-in-differences regressions. Similarly, the interpretation of the Diff-in-disc results follow the same path, with the only distinction of naming *Below* the eligible group, since it refers to the position regarding the threshold.

Secondly, each sample is matched according to the same covariates, but specific to the different outcome variables. The matching process is further explained in Section 3.5 and then reported in the Appendix C1. The variables of interest used are the same across all regressions, with an additional control of the distance to the threshold for what concerns the discontinuity.

The tables are presented in a thematic fashion, starting from a well-being analysis, going to labour market participation, and concluding with a heterogeneity analysis. Estimation methods are presented pairwise, in order to ensure comparability of results where possible. Additional material is relegated to the appendices. In Appendix C1, Table C1.1 presents the estimates of delivering a *fake treatment* in 2018, and since the treatment coefficients are not statistically different from zero for all the outcome variables, this is a powerful tool to make the diff-in-diff approach robust. Figure C1.4 gives the intuition of the RdC dynamics, through two distinct event studies. In Appendix C2, Figure C2.2 sketches graphically the jump at the discontinuity for all the outcome variables, where it happened. In addition, another diff-in-disc estimation is presented in Table C2.1, to make the income cutoff results

comparable with the ISEE fixed threshold.

3.6.1 Effects on Well-being

The first metrics analysed concern the well-being domain. This relates to a direct evaluation of the programme, since consumption and poverty are the key dimensions of the intervention. Consumption analysis is a novelty in the literature of Italian MIS, and poverty is here twofold, relative and absolute. The former is defined at European level, when the household income is lower than the 60% of the national median income, while the latter is specifically calculated from ISTAT (according to the family size, age, location of residence and home-ownership status) for each household cohort.

The results reported in Table 3.4 provide compelling evidence on the effectiveness of the RdC in reducing both poverty dimensions and sustaining consumption among beneficiaries. This fact highlights the effective targeting of the programme towards households at the bottom of the consumption distribution. The highly significant coefficients on the *Eligible / Below* group confirm that, even before receiving the benefit, eligible households exhibited significantly lower consumption levels and higher poverty risk compared to the general population.

The $Post - Treatment$ coefficients suggests an upward trend in consumption over the period 2019–2023, possibly linked to macroeconomic recovery or broad stimulus measures during the Covid-19 years, and a generally nuanced variation in poverty levels. The years of implementation was subject to multiple shocks and ambiguous economic cycles, highlighting the importance of this measure.

The Difference-in-Differences estimates, enhanced by propensity score weighting, yield statistically significant negative treatment effects on poverty: the RdC reduced relative poverty by approximately 5.2 percentage points (coefficient on $Treated$ = -0.052, SE = 0.014) and absolute poverty by 4.3 percentage points (coefficient = -0.043, SE = 0.014). These results indicate a substantial improvement in the living conditions of treated households relative to comparable non-recipients, consistent with what is typically found in the evaluation of targeted minimum income schemes (see Figari et al. (2013); Curci et al. (2020)). Alongside, consumption increased by almost 4% (coefficient = 0.039, SE = 0.016). These findings are consistent, since we explored two sides of the same coin: the subsidy was devoted to the lower bound of income distribution, where the material deprivation exists and

Table 3.4: Regression results on poverty and consumption.

	PSM-DiD			Diff-in-Disc		
Variable	Cons.	Rel.Pov.	Abs.Pov.	Cons.	Rel.Pov.	Abs.Pov.
Eligible/Below	-0.300***	0.216***	0.175***	-0.041***	0.146***	0.098***
	(0.015)	(0.013)	(0.013)	(0.010)	(0.008)	(0.008)
Post-T.period	0.048***	-0.019***	0.001	0.016***	-0.008***	0.013***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Treated × Post	0.039**	-0.052***	-0.043***	0.041***	-0.062***	-0.022***
	(0.016)	(0.014)	(0.014)	(0.010)	(0.009)	(0.008)
Retired	0.030***	-0.004	-0.033***	0.010**	0.016***	-0.010***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Children	0.138***	-0.048***	-0.043***	0.155***	0.006*	-0.014***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
Age (avg)	-0.377***	-0.060***	-0.006	-0.245***	-0.088***	-0.050***
	(0.017)	(0.014)	(0.012)	(0.013)	(0.009)	(0.008)
Married	0.025***	-0.005*	-0.003	0.016***	-0.005*	-0.005**
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Single	-0.386***	-0.152***	-0.055***	-0.436***	-0.071***	-0.015***
	(0.007)	(0.005)	(0.005)	(0.004)	(0.003)	(0.002)
Family(5+)	0.136***	0.113***	0.092***	0.120***	0.163***	0.128***
	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)
Rent	-0.314***	0.184***	0.133***	-0.294***	0.109***	0.077***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Urban	0.033***	-0.014***	0.003	0.052***	-0.009***	0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Education	0.817***	-0.429***	-0.259***	0.652***	-0.231***	-0.157***
	(0.009)	(0.008)	(0.007)	(0.007)	(0.005)	(0.004)
Constant	9.984***	0.386***	0.221***	9.998***	0.287***	0.187***
	(0.012)	(0.010)	(0.008)	(0.011)	(0.008)	(0.007)
Distance				0.146***	-0.035***	-0.033***
				(0.003)	(0.002)	(0.002)
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
N	109,855	109,855	109,855	131,705	131,705	131,705
AIC	134,950	95,110	57,581	162,942	80,391	52,116
R^2	0.345	0.175	0.108	0.415	0.219	0.126

Notes: Estimation performed using the two methodologies indicated in the first row. The discontinuity is at the relative income threshold of each household, spanning from €6,000 to €20,592. The dependent variables are reported in the second row. Standard errors are reported in parentheses.

*** Significant at 1 percent. ** Significant at 5 percent. * Significant at 10 percent.

the consumption is mainly of subsistence.

The diff-in-disc regressions confirm all those results, simply by a slightly different magnitude due to the slightly different statistical design. *Consumption* (coefficient = 0.041, SE = 0.010) and *Relative Poverty* (coefficient = -0.062, SE = 0.009) are well aligned, while *Absolute Poverty* is lower (coefficient = -0.022, SE = 0.008), but its distribution is skewed away from the threshold. All the estimations are performed with the inclusion of regional fixed effects, with the Lazio region (Rome) as benchmark.

Moreover, Figure C1.4 (in Appendix C1) gives a glance on the implementation dynamics of the measure. Introduced in April 2019, shortly succeeded by the pandemics, it started being effective after some months, but the pattern is clear. In the last years analysed, the evidence of larger expenditure levels and lower poverty risk becomes stable and statistically significant.

Importantly, the inclusion of several socio-demographic controls allows for a meaningful interpretation of the well-being impacts. Tenancy (*Rent*) and living in the South are all associated with significantly higher probabilities of being in poverty and lower expenditures, highlighting structural vulnerabilities - typical of the Italian context. The family size also plays a pivotal role: $Large families(5+)$ are structurally more exposed to vulnerability, even though the consumption level is higher due to large number of components. In contrast, *Single* households exhibit negative coefficients on poverty, which might at first appear counterintuitive, but they could reflect that many single-person households are retirees with stable pensions. Consequently, household composition factors, such as being *Married* or older ($Age(avg)$), reduce poverty likelihood and are associated with higher expenditures, as well as higher educational attainment (*Education score*). Once controlling for regional fixed effects, living in city ($Urban$) seems to play a secondary role, even if it is positively associated with consumption and negatively to poverty.

Overall, these findings reinforce the typical narrative in the literature that minimum income schemes, by design, channel resources toward the most economically fragile groups, leading to statistically and economically meaningful reductions in poverty indicators (Gallo and Raitano (2019); Sacchi et al. (2023)); at the same time, providing clear evidence that the RdC boosted subsistence consumption, consistent with theoretical predictions that income transfers to low-income households raise consumption due to liquidity constraints (Jappelli & Pistaferri, 2010), though often with a magnitude smaller than the theoretical marginal propensity to consume would suggest. The modest elasticity points to possible smoothing

behaviour, debt repayment, or unobserved informal spending — typical considerations in evaluating the broader welfare impacts of means-tested income support. Moreover, the results underline how persistent socio-demographic factors continue to shape the risk of poverty beyond the intervention itself.

3.6.2 Effects on Labour market

The other main goal mentioned in the introduction of the scheme was the establishment of a labour activation policy. Italy suffers from decades of a stagnant labour market, with relatively high unemployment rates - especially among young people - and lower employment rates with respect to the other main EU countries. There was a huge political debate about the effectiveness of RdC as an active labour policy. The measure traced a compromise between the political parties forming the coalition government. Indeed, some criticisms arose already during the implementation, as elucidated by the Valuation Committee (AA.VV., 2021). We explore three mutually exclusive metrics, such as being *Unemployed*, *Employed* or *Inactive* - the latter defined in residual way, with the exclusion of retired people. Since they are family indicators, they could be interpreted as household-level shares.

The regression results presented in Table 3.5 provide clear evidence that the RdC had a statistically significant effect on labour variables. The PSM-DID coefficient on the *Treated* variable for *Unemployment* is 0.061 (SE = 0.008), indicating that, on average, the programme increased the share of unemployed household members by approximately 6.1 percentage points among recipients compared to the control group. On the other side, *Employment* decreased analogously by 6.1 p.p. (coefficient = -0.061, SE = 0.007). *Inactive* rate appears less pronounced, with a coefficient of 0.016 (SE = 0.007).

The diff-in-disc results are somewhat varied and nuanced, with no statistical significancy on *Unemployment*. The other metrics also display lower magnitude in general, with an mild negative impact on *Employment* (coefficient = -0.013, SE = 0.005) and slight positive effect on *Inactivity* (coefficient = 0.016, SE = 0.005). These results highlight the importance of those dimensions away from the threshold.[16]

The positive and significant coefficient on the *Eligible* group (0.092), and opposite negative for employment, highlights that, even among those who did not receive the benefit but would have been eligible, the baseline unemployment share was substantially higher than

[16]Indeed, in other regressions not reported here for reasons of length, artificially lowering the threshold to €3,000, yields to significant results in line with the PSM-DiD estimates.

Table 3.5: Regression results on labour market outcomes.

	PSM-DiD			Diff-in-Disc		
Variable	Unempl.	Employ.	Inactive	Unempl.	Employ.	Inactive
Eligible/Below	0.094***	-0.092***	-0.003	0.051***	-0.029***	-0.048***
	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)
Post-T.period	-0.023***	0.039***	-0.011***	-0.008***	0.006***	0.011***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Treated × Post	0.061***	-0.061***	0.016**	0.004	-0.013**	0.016***
	(0.008)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
Retired	-0.049***	-0.242***	-0.120***	-0.028***	-0.417***	-0.225***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
Children	-0.081***	-0.064***	0.108***	-0.085***	-0.275***	0.284***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Age (avg)	-0.050***	-0.294***	-0.145***	-0.116***	-0.641***	0.380***
	(0.007)	(0.009)	(0.010)	(0.005)	(0.008)	(0.008)
Married	-0.015***	0.018***	-0.004***	-0.017***	0.011***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Single	-0.032***	0.103***	-0.159***	-0.042***	0.081***	-0.137***
	(0.004)	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)
Family(5+)	0.013***	-0.084***	0.076***	0.013***	-0.092***	0.086***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Rent	0.032***	-0.006***	-0.025***	0.014***	0.018***	-0.027***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Urban	-0.002*	0.003**	-0.000	0.002	-0.010***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education	0.010***	0.410***	-0.302***	0.009***	0.311***	-0.260***
	(0.004)	(0.005)	(0.005)	(0.002)	(0.004)	(0.004)
Constant	0.151***	0.325***	0.632***	0.184***	0.691***	0.291***
	(0.005)	(0.006)	(0.006)	(0.004)	(0.006)	(0.005)
Distance				-0.035***	0.063***	-0.044***
				(0.001)	(0.001)	(0.001)
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
N	109,855	109,855	109,855	131,705	131,705	131,705
AIC	77,371	38,406	41,736	96,675	679	25,244
R^2	0.143	0.374	0.350	0.151	0.584	0.485

Notes: Estimation performed using the two methodologies indicated in the first row. The discontinuity is at the relative income threshold of each household, spanning from €6,000 to €20,592. The dependent variables are reported in the second row. Standard errors are reported in parentheses.

*** Significant at 1 percent. ** Significant at 5 percent. * Significant at 10 percent.

in the general population. This underscores the successful targeting of the policy towards households already structurally more exposed to labour market fragility, a typical feature noted in studies on minimum income schemes (Immervoll et al. (2007); Busilacchi and Fabbri (2024)).

Interestingly, the coefficient $Post{-}Treatment$ is negative, while positive for $Employment$, suggesting a mild overall positive labour trend throughout the years covered, possibly linked to macroeconomic recovery phases post-Covid which is controlled for. These findings are in line with the general trend presented also in Table 3.4.

The socio-demographic controls included in the regression help to explain the heterogeneity of household labour force. The control variables of being family head $Retired$ or having $Children$ are associated with significantly lower unemployment shares. This aspect could likely reflect the effects of life-cycle model. The variables Age and $Married$ also confirm this pattern. In contrast, being $Tenant$ or part of a $Large family$, especially if living in the South, increases the probability of unemployment, consistent with structural disadvantages documented in Italian labour markets. The coefficient on $Education$, although positive, is small, suggesting complex interactions possibly tied to over-education phenomena or regional labour mismatches. Finally, also the city size ($Urban$) does not strongly affect the outcomes.

Taken together, these findings resonate with the literature on means-tested minimum income schemes, which often notes small but significant disincentives to formal labour participation, particularly when activation requirements are weak or when the transfer design lacks time limits (Curci et al. (2020); Immervoll et al. (2007)). Particularly, in a relatively fragmented, immobile, and informal labour market - for being a developed OECD-Country - like in the Italian case, caution is needed in both policy design and evaluation. Our findings highlight the importance for policymakers to carefully balance poverty alleviation objectives with incentives for re-employment, potentially through stronger activation measure, coordinated with a territorially granular labour system, and with gradual benefit tapering mechanisms.

3.6.3 Heterogeneity analysis

The benefit was diversified according to the household structure, and this subsection intends to explore possible heterogeneous effects among recipient families. It followed the equivalence scale properly established by law for this measure. The primary dimension is represented by

Table 3.6: Heterogeneous Effects by Household Type

	Single		Large family		Tenants		Home-owners	
Variable	DiD	DiDC	DiD	DiDC	DiD	DiDC	DiD	DiDC
Consumption	-0.007	0.043**	0.076**	0.082***	0.057***	0.025**	0.020	0.023*
	(0.043)	(0.020)	(0.030)	(0.017)	(0.022)	(0.011)	(0.036)	(0.013)
Rel. Poverty	-0.049	-0.049***	-0.081***	-0.063***	-0.060***	-0.056***	-0.057	-0.001
	(0.037)	(0.014)	(0.026)	(0.016)	(0.019)	(0.010)	(0.038)	(0.011)
Abs. Poverty	0.019	-0.013	-0.052*	-0.041***	-0.036*	-0.011	-0.074**	-0.015*
	(0.033)	(0.013)	(0.027)	(0.016)	(0.019)	(0.009)	(0.034)	(0.009)
Unemployment	0.108***	0.034**	0.098***	-0.010	0.049***	0.017***	0.130***	-0.023***
	(0.031)	(0.014)	(0.008)	(0.006)	(0.010)	(0.005)	(0.017)	(0.007)
Employment	-0.098***	-0.025*	-0.069***	-0.021***	-0.065***	-0.027***	-0.082***	0.032***
	(0.032)	(0.015)	(0.008)	(0.005)	(0.010)	(0.006)	(0.018)	(0.007)
Inactivity	-0.015	-0.010	-0.019**	0.035***	0.027***	0.020***	-0.014	0.008
	(0.026)	(0.012)	(0.008)	(0.006)	(0.010)	(0.005)	(0.017)	(0.007)
Control Variables	Yes		Yes		Yes		Yes	
Regional FE	Yes		Yes		Yes		Yes	
N	6,661	31,075	19,572	45,851	29,344	54,535	65,352	226,239

Notes: Estimation performed using diff-in-diff and diff-in-disc regressions. The dependent variables are reported in the first row. Standard errors are reported in parentheses. Same control variables and regional fixed effects are added at each regression.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

the family size. The *Single* category is the unitary value of the equivalence scale, so the lower bound also in monetary terms. Each additional adults increased the scale by 0.4, while each minor only by 0.2. Large households are instead the upper bound of the equivalence scale. The second aspect is the housing status, because a rental condition granted an extra-revenue, due to the higher vulnerability of the renting households.

The logic of this analysis is to deepen the impact analysis on beneficiaries, based on the differentiated monetary amounts perceived by households. The comparison is done pairwise, taking two extreme mutually exclusive situations. Firstly, unitary component households with respect to large families, with five or more members; second, confronting tenancy with housing property.

Starting from the family size comparison, the larger effects on well-being as the magnitude of the amount increases becomes evident. Indeed, while *Single* show a modest increase in consumption and decrease in poverty levels, $Large\ families$ experienced on average significant boost in essential expenditure levels and a stronger reduction of poverty risk.

The comparison between $Tenants$ and $Home-owners$ confirms the previous statement. The former exhibit systematically better results than the latter, with the only exception of consumption-based poverty. This is probably due to the fact that rental expenditures - relevant part of the budget share - contributes to a higher exposure to poverty risk, while

the relative poverty is only defined with respect to income, in this case augmented by to the subsidy.

The labour force effects are more nuanced and ambiguous. A first issue is certainly their non monetary nature, along with the presence of smaller samples regarding the general analysis. We could evinced from the estimates that the amount also plays a role in the labour dynamics. The unemployment household share tends to be lower when the subsidy is larger, whilst the employment share experiences the other way around. Moreover, the diff-in-diff estimates show larger effects over the entire distribution[17], meanwhile the coefficients are smaller around the point of discontinuity. Interestingly, inactivity instead seems to be positively correlated with the magnitude of the amount, and this fact might be aligned with the Neoclassical economic theory.

Overall, the impact on economic variables, like consumption and poverty, is clearer than on the working situation. Despite the fact that the analysis is run with limited samples, those findings suggest then the amount of the transfer matters. Only when the transfer increases, the measure is able to reach its goals. A larger magnitude intuitively yields stronger effect in boosting consumption and reducing poverty. The labour market effects are more shaded, but the amount heterogeneity seems to play some role also in mitigating the working drawbacks.

3.7 Conclusive Remarks and Policy Implications

This paper provides robust empirical evidence on the multidimensional welfare effects of Italy's Citizenship Income (RdC), analysing its impacts on poverty, household consumption, and labour market variables. Exploiting a rich dataset that combines survey and administrative records over the period 2017–2023, we apply a rigorous difference-in-differences framework with propensity score matching, complemented by a difference-in-discontinuity approach to address potential selection bias issues on eligibility thresholds.

Our results show that the RdC significantly reduced both income-based relative and consumption-based absolute poverty, lowering the former measure by 5 percentage points and the latter by 4 points among recipients. These findings underline the effectiveness of the programme in alleviating material deprivation and improving the living standards of low-income households. They are consistent with the existing literature on minimum income schemes in Italy (e.g., Gallo and Raitano (2019); Curci et al. (2020); Sacchi et al. (2023)),

[17] In this case, it refers to the lower brackets of the income distribution.

which documents substantial reductions in poverty and inequality following the introduction of the RdC. It is a confirmation that such programmes effectively support the lower end of the income and consumption distribution, providing a critical safety net for households most vulnerable to economic shocks.

Moreover, we find that the RdC increased aggregate household consumption by approximately 4%, playing a stabilising role especially during the economic disruptions of the Covid-19 period. This result aligns with economic theory and international evidence suggesting that transfers to low-income, liquidity-constrained households typically translate into high marginal propensities to consume (Jappelli & Pistaferri, 2010). The increase in consumption underlines the direct welfare gains for recipient households, improving their ability to maintain adequate living standards and smooth consumption in the face of income shocks. At the same time, it highlights the role of such schemes as automatic stabilisers, sustaining aggregate demand during periods of economic downturn - a mechanism that proved particularly important during the Covid-19 crisis.

However, the analysis also reveals a modest rise in unemployment of about 6 percentage points among beneficiaries, along with a corresponding decrease in the employment share and a mild increase in inactivity. Several mechanisms could underlie this outcome: the lack of possible integration with any form of work, as highlighted by the scientific committee for the evaluation of RdC (see AA.VV. (2021)), the lack of strong activation requirements and time limits which may reduce the urgency to seek formal employment, while in some cases benefits might interact with informal work, especially in contexts with high undeclared labour shares.

Our findings help to reframe the Italian debate, often shaped by anecdotal claims suggesting widespread inactivity or welfare dependency, by providing a more evidence-based understanding of how the programme has performed. Building on this empirical picture, the findings also offer guidance for ongoing policy developments: they provide an empirical foundation for the design of future minimum income scheme reforms in Italy, notably since that the scheme has been recently changed[18], and position the Italian experience within a broader European policy context characterised by the EU's long-standing commitment to adequate and inclusive minimum income schemes, the principles of the European Pillar

[18] *Assegno di Inclusione* is the minimum income scheme introduced in Italy in 2024, targeted at households with children, elderly or vulnerable members and combining income support with activation requirements. *Supporto per la Formazione e il Lavoro* is a parallel activation programme for work-eligible individuals, offering a participation allowance conditional on enrollment in training, job-search, or work experience activities.

of Social Rights, and the recent Council Recommendation on ensuring effective access to minimum income and active inclusion.

The multidimensional evidence presented in this paper carries several important policy implications for the design of future minimum income schemes in Italy. First, the sizeable reductions in both income-based and consumption-based poverty, together with the meaningful increase in household expenditure, confirm that non-contributory transfers remain an essential component of the Italian welfare architecture, particularly for households facing persistent structural disadvantages. Yet the observed increase in unemployment among recipients signals that the effectiveness of such schemes depends crucially on their integration with well-functioning activation strategies. The RdC experience shows that income support without strong, credible pathways into employment may generate mild work disincentives, especially in areas with weak labour demand and fragmented institutional capacity. Therefore, policy reforms should prioritise the strengthening of public employment services, the introduction of gradual benefit tapering to avoid sharp eligibility cliffs, and the development of earnings disregards that reward partial or irregular work without jeopardising eligibility. At the same time, territorial disparities in the incidence of need and in administrative capacity suggest that a *one-size-fits-all* design is unlikely to be effective; decentralised implementation, accompanied by adequate funding and local capacity building, may be necessary to ensure equitable access and outcomes across regions.

In conclusion, the findings underscore the need to evaluate minimum income schemes not solely through the lens of labour supply, but within a broader welfare framework that recognises their stabilising role during shocks and their capacity to alleviate material deprivation. The challenge for policymakers is therefore to calibrate minimum income scheme in a way that preserves their strong anti-poverty impact while improving labour force integration, an objective which implies complex inherent trade-offs that require better coordination between income support, activation services, and local labour market conditions. Future research should involve potential long-term impacts on labour dynamics and the evolution of informal work, the broader general equilibrium effects on local economies, the change of preferences in consumption, and the effect of the overcoming of RdC on poverty and inequality.

Appendix A

Literature review resume

Table A.1: Resume table of the empirical papers analysed in Chapter I

Authors	Data	Results and implications
	Engel Curves	
E. Engel (1857)	200 Belgian households	Engel's Law: as income rises, the budget share devoted to food tends to decrease.
Chai and Moneta (2010)	E. Engel (1857) data	They replicated the original study of Engel and highlighted the innovative design.
Moneta and Chai (2014)	UK household expenditure 1968-2006	They focused on the saturation of consumption beyond a certain income level; the curves are flattening over income distribution.
Aguiar and Bils (2015)	1980-2010 CEX	They concluded that U.S. consumption inequality has risen almost as much as income inequality since 1980.
Chai et al. (2015)	UK microdata	Low-income families are homogeneous and oriented toward subsistence consumption, while high-income level expenditures are strongly heterogeneous, both in terms of aggregate level and of variety.
Li (2021)	1983-2009 Indian microdata	Households with higher expenses tend to consume a wider set of varieties.

Continue to the next page

Authors	**Data**	**Results and implications**
Clements and Si (2018)	31 food categories in 150 countries	Higher income is associated with greater dietary diversity and quality; the elasticity of diversity to income is ~ 0.3.
Comin et al. (2021)	1999-2010 CEX	They found that income effects explain most within country sectoral reallocation, and services display higher income elasticities, agriculture lower, manufacturing in between.
Clements et al. (2022)	Australian microdata	The income quintiles can capture most of the nonlinearity and the diversity of consumption patterns.
De Vreyer et al. (2020)	Senegalese data	The Engel curves are not distorted if all the family members experience a proportional rise in income and the individual preferences are separable.
Atkin et al. (2024)	Two waves (1987, 2000) in rural India	They studied income-specific price indices and non-parametric estimation of relative Engel curves; a welfare measurement should account for heterogeneous price exposure.
Sologon et al. (2025)	HBS data, 2021-22 Europe	Inflation acted as a regressive tax with a disproportionate burden on vulnerable households.
	Quasi-experimental MPC	
Bodkin (1959)	1950 CEX	MPC of non-durables out of the shock was as high as 0.72, a strong violation of the permanent income model.
Wolpin (1982)	1968-71 panel rural Indian households	Permanent income elasticity estimates ranged from 0.91 to 1.02, supporting the permanent income model.

Continue to the next page

Authors	**Data**	**Results and implications**
Paxson (1993)	1975-76, 1981, 1986 Thai-SES	High propensity to save out of transitory weather shocks, but also a propensity to save out of permanent shocks above zero.
Gruber (1997)	1968-1987 PSID	Unemployment insurance had a large smoothing effect for unanticipated layoffs.
Browning and Crossley (2001)	1993 Canadian-COEP	Elasticity of expenditures with respect to unemployment benefit was 5%, but 20% for low-asset individuals.
Gertler and Gruber (2002)	1991, 1993 Indonesian-IRMS	People smoothed well the effect of minor illnesses (interpreted as transitory shocks), but less the effect of major illnesses (permanent shocks).
	Self-reported MPC	
Shapiro and Slemrod (1995)	Telephone Survey 1992	40% of the people interviewed planned to spend the extra take-home pay.
Shapiro and Slemrod (2003)	Surveys in 2001-02	22% of the interviewed households reported planning to spend the tax rebate, little evidence of myopia or liquidity constraints.
Shapiro and Slemrod (2009)	Survey 2008	20% of survey respondents said that the 2008 tax rebates would lead them to mostly increase spending.
Johnson et al. (2006)	2001 CEX	Average household spent 20-40% of the rebate on non-durable goods; expenditure responses were largest for liquidity constrained.
Parker et al. (2013)	2008 tax rebate	Households spent between 50% and 90% of the transfer, among which 12%-30% in non-durables and a general rise of durables (vehicles); the effect was stronger for low-income, older or home-owner households.

Continue to the next page

Authors	**Data**	**Results and implications**
Jappelli and Pistaferri (2014)	SHIW 2010	They found evidence of a strong decline in MPC over the income distribution, with a total average of 0.48.
Jappelli and Pistaferri (2020)	SHIW 2016	Results confirmed MPC declines with resources availability and liquid assets as its key drivers.
Albacete et al. (2025)	HFSC (ECB)	Wide heterogeneity across agents and countries: the total average is 0.46, and the patterns within nations are systematic, with cash-on-hand households displaying higher MPCs.
Christelis et al. (2019)	2015 Dutch CentER	Asymmetry between positive and negative shocks, with stronger responses in the latter case.
Immordino et al. (2022)	SCC 2020	The fear of COVID-19 contagion and the income uncertainty caused a drop in consumption, and a relative increase in savings.
	Semi-structural model	
Hall and Mishkin (1982)	1969-75 PSID	The response of consumption to innovations in transitory income was 29% (too high to be consistent with the theory).
Attanasio and Weber (1995)	1980-90 CEX	Failure to control for labor supply indicators may lead to spurious evidence of excess sensitivity.
Parker (1999)	1980-93 CEX	1 dollar anticipated rise in income increased non-durable consumption by about 20 cents.
Souleles (1999)	1980-91 CEX	10% of the refunds were spent on non-durables and 65% on total consumption, suggesting that most of the refund was spent on durables.

Continue to the next page

Authors	**Data**	**Results and implications**
Blundell et al. (2008)	1978-92 PSID, 1980-92 CEX	Consumption was nearly insensitive to transitory shocks, and response to permanent shocks was significantly lower than 1, suggesting that households are able to partially insure permanent shocks.
Stephens (2008)	1984-2000 CEX	A 10% increase in discretionary income leads to a 2% to 3% increase in nondurable consumption.
Misra and Surico (2014)	2001-08 tax rebates	Low-income households and tenants showed a high tendency to spend; the heterogeneity of consumption is concentrated in few nondurable and durable categories.
Bernheim et al. (2001)	1978-90 PSID, CEX	Substantial consumption drop at retirement (24% first income quartile, 15% second, 9% other quartiles).
Lewis et al. (2024)	2008 tax rebate	Household observable characteristics explain only 8% of MPC variation; the other part highlights the role of latent heterogeneity.
J. D. Fisher et al. (2020)	1999-2013 PSID	MPC is lower at higher wealth quintiles, while low wealth households cannot smooth consumption. The implication is that increasing wealth inequality likely reduces aggregate consumption.
Mian et al. (2013)	2006-09 retail prices	The estimated consumption-wealth elasticity is about 0.6-0.8, with a strong wealth effect (similar to a permanent income), stronger for low-income or indebted households.
Campbell and Cocco (2007)	British retail prices	The results highlights a direct price effect and the heterogeneity of the wealth effect (permanent income).

Continue to the next page

Authors	**Data**	**Results and implications**
Carroll et al. (2017)	Model calibration	Estimated average MPC (0.20) depends critically on the distribution of shock recipients and is not a structural constant of the economy.
Fagereng et al. (2021)	Norwegian lottery data	They found that MPCs are close to unity ($\simeq 1$) for small prizes and liquidity-constrained households, but decline sharply (≤ 0.5) with greater wealth, age, and prize size.
Kaplan and Violante (2022)	HANK systematic review	Empirically realistic MPCs range from 0.2 to 0.6, close to 1 for hand-to-mouth (also wealthy). Empirical estimates suggest MPCs of 0.25 (0.15) following transitory income shocks of \$1,000 (\$500).
	Price elasticity	
Andreyeva et al. (2010)	1938-2007, 160 U.S. studies	Food demand is generally inelastic, with mean absolute elasticities from ~ 0.27 to ~ 0.81, with disaggregated category very diversified. Large price changes are required to induce sizeable consumption responses.
Cornelsen et al. (2015) and Green et al. (2013)	78 articles - 38 countries	Demand is generally more price-responsive in low-income countries, and cross-price effects vary with development level and dietary diversity. In high-income settings, richer substitution or complementarity patterns emerge. The one-size-fits-all could be misleading.
Jensen and Miller (2008)	2006 Chinese NBS	Experiment on staple food about Giffen goods in China, under conditions of tight budget constraint and inferior-good dynamics.

Continue to the next page

Authors	**Data**	**Results and implications**
Alberini et al. (2011)	1997-2007 RECS	The own price elasticity of electricity is around -0.8, while the one of the gas demand is -0.6. They found strong household response to energy prices.
Hastings and Shapiro (2013)	1990-2009 EIA, 2006-09 CEX	When the oil price goes up, consumers tend to lower the quality with cheaper gasoline, due to not only to income effect but also to mental accounting. The authors explain that with behavioural theory, since consumers are not perfectly rational.
Labandeira et al. (2012)	2005-07 Spanish *Iberdrola*	The energy demand is on average inelastic in the short-run, and it becomes more rigid for rich households and big firms.
Labandeira et al. (2017)	Meta-analysis	They report evidence of short-run price elasticity around -0.21, and long-run around -0.61, but with substantial heterogeneity.
Coglianese et al. (2017)	1989-2008 gasoline tax	The estimated gasoline demand elasticities are reasonably lower in presence of taxes or time leads/lags (-0.37) because of the possibility of stockpiling or delayed expenditure.
Belaïd et al. (2020)	2014 PHEBUS	They found evidence of price elasticity around 0.38-0.71 and efficiency elasticity 0.72-0.86, with substantial heterogeneity among quantiles.
Hahn and Metcalfe (2021)	CARE subsidy	They estimated a natural gas price elasticity of around -0.35 for low-income households.
Trotta et al. (2022)	Denmark residential heating	Price elasticities are heterogeneous according to several dimensions: single households display higher coefficients, large consumers are more elastic, and poor families are more reactive.

Continue to the next page

Authors	**Data**	**Results and implications**
Liddle and Huntington (2020, 2021)	78 countries - 50 years	For high-income countries, the energy elasticity is around -0.22 in the long run, while developing countries exhibit elasticity close to zero, along with a higher income elasticity.
Gao et al. (2021)	Liddle and Huntington (2020) data	They confirmed an energy price elasticity between -0.1 and -0.3, with a different nonlinear econometric approach.
Peersman and Wauters (2024)	NBB Belgian households survey	They estimate the energy elasticity and MPC after an energy shock: asymmetric responses, stronger for price hikes (-0.36) than to decreases (-0.07); elasticity lower for larger shocks (-0.29 instead of -0.43). Responsiveness is higher among low-income households, and the MPC is 0.59 for the rise and 0.40 for the fall in prices.
Priesmann and Praktiknjo (2025)	2023 SOEP, MOP	They examined the elasticity of domestic energy consumption, considering income heterogeneity: low-income families have a short-run energy elasticity of -0.27 and a long-run of -0.22; high-income families, respectively, of -0.44 and -0.64.
Miller and Alberini (2016)	1997-2009 AHS	They analysed the sensitivity of the price elasticity to methodology and data, explaining the estimates variation with aggregation issues, unobserved heterogeneity, and missing variables. For these reasons, it is necessary to control for permanently divergent aspects to avoid bias or overestimation.
Bobasu et al. (2025)	HANK model	The energy-price shocks have regressive impacts and interact with monetary policy, since the rise in interest rate could amplify the effect.

Equations of consumer demand models

1. Budget share equations (Deaton, 1985):

$$e_{i,h,t}(j) = f_j(y_{i,h,t}, s_{h,t}) \tag{A.1}$$

$$log(e_{i,h}(j)) = \alpha(j) + \beta(j) log(y_{i,h}) + \sum_{l=1}^{L} \gamma_l(j) s_h + \epsilon_i(j) \tag{A.2}$$

$$Elasticity = \beta_j = \frac{\Delta e_j}{\Delta y} \frac{y}{e_j} \tag{A.3}$$

2. Houthakker (1950) demand function:

$$\ln C_{i,j} = \alpha_i + \beta_i \ln Y_j + \gamma_i \ln N_j + \varepsilon_{i,j} \tag{A.4}$$

3. Working (1943) - Leser (1963) demand function and expenditure elasticities:

$$w_i = \alpha_0 + \alpha_i \log x + \sum_j \beta_{ij} \log p_j + \sum_k \gamma_{ik} H_k + \varepsilon_i \tag{A.5}$$

$$e_i = 1 + \left(\frac{\alpha_i}{w_i}\right) \tag{A.6}$$

$$e_{ij} = -\delta_{ij} + \left(\frac{\beta_{ij}}{w_i}\right) \tag{A.7}$$

4. The LA/AIDS model equations (Deaton & Muellbauer, 1980):

$$w_i = \alpha_i + \sum_j \gamma_{ij} \ln(p_j) + \beta_i \ln\left(\frac{x}{P}\right) + \mu_i \tag{A.8}$$

$$e_i = 1 + \left(\frac{1}{w_i}\right)\left(\frac{\partial w_i}{\partial \ln x}\right) = 1 + \left(\frac{\beta_i}{w_i}\right) \tag{A.9}$$

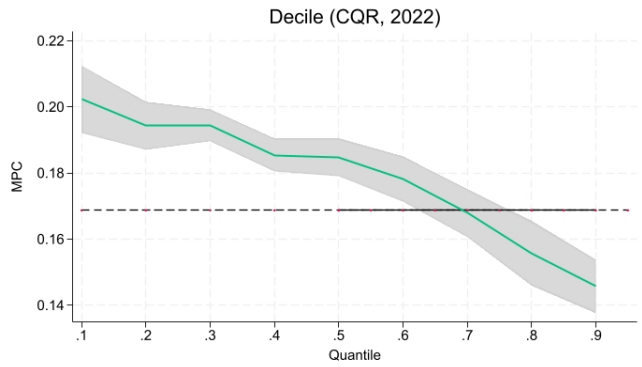
5. The QUAIDS equation (Banks et al., 1997):

$$w_i = \alpha_i + \beta_i \ln x + \gamma_i (\ln x)^2 + \sum_j \lambda_{ij} \ln p_j \tag{A.10}$$

Appendix B1

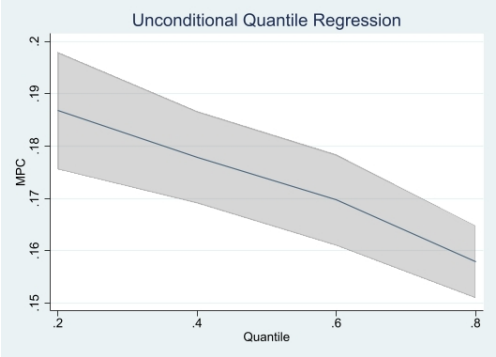
Comparison of OLS and QR estimations

Figure B1.1: Conditional quantile regression



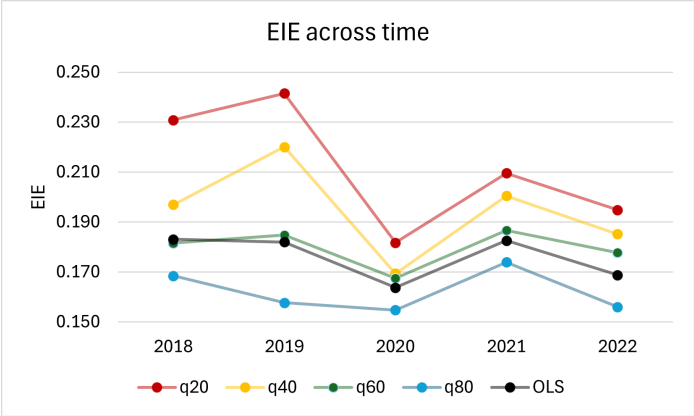
Notes: Figure shows the trend of elasticity throughout conditional quintiles. The line shows the coefficient values of log(Y) and the confidence interval.

Figure B1.2: Unconditional Q.R.



Notes: Figure shows the trend of elasticity throughout unconditional residualised quintiles (Borgen et al., 2022). The line shows the coefficient values of log(Y) and the the confidence interval.

Figure B1.3: EIE estimation over time



Notes: Figure shows the trend of elasticity throughout the years analysed. Each coloured line refers to a different quintile, while the black one is the OLS-benchmark. It reflects Table 2.9.

OLS and Quantile regressions across time

Table B1.1: OLS yearly regression (2018-2022)

Variable	2018	2019	2020	2021	2022
log(Y)	0.183***	0.182***	0.164***	0.183***	0.169***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Unemployed	0.050**	-0.065***	0.000	0.068***	0.097***
	(0.020)	(0.022)	(0.014)	(0.017)	(0.017)
Retired	-0.201***	-0.179***	-0.146***	-0.124***	-0.087***
	(0.012)	(0.012)	(0.009)	(0.009)	(0.009)
Urban	0.084***	0.061***	0.080***	0.083***	0.089***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Male	0.001	-0.002	-0.019***	-0.011***	-0.013***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Married	0.052***	0.044***	0.053***	0.054***	0.078***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)
Age (<30)	0.027*	0.036**	0.037***	0.091***	0.096***
	(0.015)	(0.015)	(0.011)	(0.011)	(0.011)
Age (30-50)	0.007	-0.002	0.019*	0.075***	0.068***
	(0.013)	(0.013)	(0.010)	(0.010)	(0.010)
Age (51-65)	0.054***	0.068***	0.056***	0.101***	0.083***
	(0.012)	(0.012)	(0.009)	(0.009)	(0.009)
Foreign-born	-0.271***	-	-0.275***	-0.271***	-0.288***
	(0.010)		(0.008)	(0.008)	(0.008)
Fixed-term contract	-0.059***	-0.068***	-0.014	-0.052***	0.075***
	(0.011)	(0.012)	(0.010)	(0.009)	(0.006)
Family size (2)	-0.297***	-0.304***	-0.352***	-0.367***	-0.364***
	(0.010)	(0.010)	(0.009)	(0.008)	(0.008)
Family size (3)	-0.543***	-0.552***	-0.586***	-0.603***	-0.598***
	(0.011)	(0.011)	(0.009)	(0.009)	(0.008)
Family size (4)	-0.692***	-0.699***	-0.754***	-0.766***	-0.755***
	(0.012)	(0.011)	(0.010)	(0.009)	(0.009)
Family size (5+)	-0.896***	-0.882***	-0.918***	-0.956***	-0.942***
	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)
North	0.030***	0.018***	0.025***	0.036***	0.037***
	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
South	-0.206***	-0.230***	-0.203***	-0.198***	-0.204***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Constant	8.167***	8.191***	8.323***	8.137***	8.266***
	(0.029)	(0.029)	(0.024)	(0.027)	(0.026)
R^2	0.388	0.366	0.398	0.399	0.406
AIC	50160.0	52812.8	61574.5	69399.1	67231.2
Observations	36,744	37,713	47,649	53,623	53,323

Notes: Estimation performed using a standard linear regression (OLS), as a benchmark estimates reference. Standard errors are reported in parentheses. The dependent variable is $log(C_{tot})$. Tests on heteroskedasticity, skewness, and kurtosis presented in Appendix B4.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B1.2: Quintile Regression in 2022

Variable	**q20**	**q40**	**q60**	**q80**
log(Y)	0.195***	0.185***	0.178***	0.156***
	(0.004)	(0.004)	(0.004)	(0.005)
Unemployed	0.102***	0.104***	0.107***	0.106***
	(0.022)	(0.019)	(0.019)	(0.029)
Retired	-0.086***	-0.077***	-0.080***	-0.098***
	(0.012)	(0.011)	(0.012)	(0.012)
Urban	0.094***	0.100***	0.095***	0.096***
	(0.005)	(0.004)	(0.005)	(0.007)
Male	-0.018***	-0.018***	-0.015***	-0.014**
	(0.006)	(0.005)	(0.005)	(0.006)
Married	0.098***	0.091***	0.067***	0.067***
	(0.008)	(0.007)	(0.008)	(0.011)
Age (<30)	0.124***	0.115***	0.100***	0.073***
	(0.016)	(0.014)	(0.013)	(0.015)
Age (30-50)	0.092***	0.080***	0.063***	0.033**
	(0.014)	(0.013)	(0.012)	(0.014)
Age (51-65)	0.094***	0.086***	0.089***	0.072***
	(0.012)	(0.012)	(0.011)	(0.011)
Foreign-born	-0.330***	-0.310***	-0.278***	-0.250***
	(0.011)	(0.010)	(0.009)	(0.014)
Fixed-term contract	0.049***	0.063***	0.086***	0.114***
	(0.008)	(0.008)	(0.008)	(0.011)
Family size (2)	-0.382***	-0.364***	-0.338***	-0.370***
	(0.011)	(0.009)	(0.011)	(0.014)
Family size (3)	-0.603***	-0.585***	-0.568***	-0.601***
	(0.011)	(0.009)	(0.012)	(0.014)
Family size (4)	-0.756***	-0.733***	-0.720***	-0.770***
	(0.012)	(0.010)	(0.012)	(0.015)
Family size (5+)	-0.951***	-0.928***	-0.893***	-0.936***
	(0.014)	(0.013)	(0.013)	(0.016)
North	0.037***	0.041***	0.039***	0.040***
	(0.007)	(0.006)	(0.006)	(0.008)
South	-0.242***	-0.224***	-0.190***	-0.155***
	(0.007)	(0.007)	(0.007)	(0.010)
Constant	7.643***	7.958***	8.241***	8.767***
	(0.046)	(0.039)	(0.039)	(0.051)
Pseudo-R^2	0.2553	0.2390	0.2259	0.2121

Notes: Estimation performed using a conditional quantile regression with 500 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{tot})$ and the quantiles are 5 (quintile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 53,310.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B1.3: Quintile Regression in 2021

Variable	**q20**	**q40**	**q60**	**q80**
log(Y)	0.210***	0.201***	0.187***	0.174***
	(0.004)	(0.004)	(0.004)	(0.004)
Unemployed	0.101***	0.0897***	0.0865***	0.110***
	(0.021)	(0.020)	(0.026)	(0.031)
Retired	-0.118***	-0.112***	-0.128***	-0.135***
	(0.011)	(0.014)	(0.011)	(0.016)
Urban	0.085***	0.091***	0.095***	0.083***
	(0.005)	(0.005)	(0.005)	(0.006)
Male	-0.017***	-0.013***	-0.012**	-0.007
	(0.005)	(0.005)	(0.005)	(0.006)
Married	0.058***	0.057***	0.056***	0.045***
	(0.008)	(0.007)	(0.007)	(0.009)
Age (<30)	0.110***	0.110***	0.087***	0.061***
	(0.014)	(0.016)	(0.015)	(0.019)
Age (30-50)	0.104***	0.099***	0.061***	0.027
	(0.013)	(0.014)	(0.013)	(0.017)
Age (51-65)	0.111***	0.115***	0.101***	0.089***
	(0.011)	(0.013)	(0.011)	(0.016)
Foreign-born	-0.294***	-0.298***	-0.273***	-0.222***
	(0.010)	(0.010)	(0.011)	(0.016)
Fixed-term contract	-0.051***	-0.036***	-0.039***	-0.039***
	(0.015)	(0.013)	(0.013)	(0.015)
Family size (2)	-0.374***	-0.367***	-0.356***	-0.359***
	(0.010)	(0.009)	(0.010)	(0.013)
Family size (3)	-0.589***	-0.586***	-0.592***	-0.620***
	(0.011)	(0.009)	(0.011)	(0.013)
Family size (4)	-0.755***	-0.746***	-0.755***	-0.766***
	(0.012)	(0.011)	(0.011)	(0.014)
Family size (5+)	-0.982***	-0.931***	-0.912***	-0.920***
	(0.015)	(0.014)	(0.014)	(0.017)
North	0.030***	0.034***	0.038***	0.041***
	(0.006)	(0.006)	(0.007)	(0.007)
South	-0.233***	-0.196***	-0.186***	-0.167***
	(0.008)	(0.007)	(0.008)	(0.009)
Constant	7.494***	7.805***	8.181***	8.613***
	(0.044)	(0.044)	(0.043)	(0.038)
Pseudo-R^2	0.2468	0.2304	0.2191	0.2118

Notes: Estimation performed using a conditional quantile regression with 500 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{tot})$ and the quantiles are 5 (quintile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 53,623.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B1.4: Quintile Regression in 2020

Variable	**q20**	**q40**	**q60**	**q80**
log(Y)	0.182***	0.169***	0.168***	0.155***
	(0.005)	(0.004)	(0.004)	(0.004)
Unemployed	0.010	-0.010	0.030	0.002
	(0.022)	(0.017)	(0.021)	(0.022)
Retired	-0.133***	-0.151***	-0.143***	-0.139***
	(0.013)	(0.012)	(0.012)	(0.016)
Urban	0.085***	0.077***	0.085***	0.092***
	(0.005)	(0.005)	(0.005)	(0.006)
Male	-0.027***	-0.019***	-0.022***	-0.015**
	(0.006)	(0.005)	(0.005)	(0.007)
Married	0.075***	0.064***	0.037***	0.017*
	(0.007)	(0.008)	(0.008)	(0.010)
Age (<30)	0.089***	0.068***	0.026*	-0.004
	(0.015)	(0.015)	(0.016)	(0.019)
Age (30-50)	0.070***	0.032**	0.002	-0.016
	(0.014)	(0.013)	(0.013)	(0.018)
Age (51-65)	0.079***	0.071***	0.053***	0.039**
	(0.013)	(0.012)	(0.011)	(0.016)
Foreign-born	-0.310***	-0.293***	-0.276***	-0.235***
	(0.011)	(0.011)	(0.011)	(0.013)
Fixed-term contract	-0.010	0.005	-0.012	-0.030**
	(0.014)	(0.010)	(0.011)	(0.013)
Family size (2)	-0.373***	-0.355***	-0.329***	-0.318***
	(0.011)	(0.010)	(0.010)	(0.014)
Family size (3)	-0.603***	-0.586***	-0.559***	-0.550***
	(0.011)	(0.011)	(0.012)	(0.014)
Family size (4)	-0.758***	-0.742***	-0.727***	-0.736***
	(0.012)	(0.012)	(0.012)	(0.014)
Family size (5+)	-0.974***	-0.899***	-0.855***	-0.856***
	(0.017)	(0.016)	(0.014)	(0.018)
North	0.017***	0.032***	0.033***	0.038***
	(0.006)	(0.006)	(0.008)	(0.008)
South	-0.224***	-0.194***	-0.188***	-0.178***
	(0.008)	(0.007)	(0.008)	(0.009)
Constant	7.762***	8.121***	8.368***	8.772***
	(0.045)	(0.038)	(0.035)	(0.040)
Pseudo-R^2	0.2341	0.2287	0.2252	0.2210

Notes: Estimation performed using a conditional quantile regression with 500 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{tot})$ and the quantiles are 5 (quintile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 47,649.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B1.5: Quintile Regression in 2019

Variable	**q20**	**q40**	**q60**	**q80**
log(Y)	0.242***	0.220***	0.185***	0.158***
	(0.005)	(0.004)	(0.004)	(0.005)
Unemployed	-0.044	-0.039	-0.0522*	-0.032
	(0.034)	(0.028)	(0.028)	(0.034)
Retired	-0.187***	-0.201***	-0.169***	-0.166***
	(0.017)	(0.016)	(0.015)	(0.016)
Urban	0.060***	0.057***	0.061***	0.069***
	(0.008)	(0.006)	(0.006)	(0.008)
Male	-0.013*	-0.011*	-0.007	-0.002
	(0.007)	(0.006)	(0.006)	(0.007)
Married	0.060***	0.044***	0.033***	0.040***
	(0.010)	(0.009)	(0.011)	(0.011)
Age (<30)	0.059***	0.033*	0.036*	0.039*
	(0.021)	(0.019)	(0.020)	(0.021)
Age (30-50)	0.012	-0.008	-0.007	-0.013
	(0.019)	(0.018)	(0.017)	(0.019)
Age (51-65)	0.070***	0.059***	0.084***	0.080***
	(0.017)	(0.016)	(0.015)	(0.017)
Fixed-term contract	-0.082***	-0.048***	-0.048***	-0.054***
	(0.020)	(0.013)	(0.015)	(0.019)
Family size (2)	-0.303***	-0.284***	-0.286***	-0.315***
	(0.014)	(0.011)	(0.014)	(0.015)
Family size (3)	-0.527***	-0.513***	-0.529***	-0.583***
	(0.015)	(0.013)	(0.016)	(0.016)
Family size (4)	-0.664***	-0.657***	-0.677***	-0.731***
	(0.014)	(0.013)	(0.016)	(0.018)
Family size (5+)	-0.863***	-0.832***	-0.807***	-0.861***
	(0.019)	(0.015)	(0.018)	(0.019)
North	0.028***	0.020**	0.023***	0.024**
	(0.010)	(0.009)	(0.008)	(0.010)
South	-0.214***	-0.224***	-0.225***	-0.227***
	(0.010)	(0.009)	(0.008)	(0.011)
Constant	7.209***	7.697***	8.251***	8.818***
	(0.054)	(0.046)	(0.042)	(0.047)
Pseudo-R^2	0.2170	0.2125	0.2049	0.1997

Notes: Estimation performed using a conditional quantile regression with 500 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{tot})$ and the quantiles are 5 (quintile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 37,713.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B1.6: Quintile Regression in 2018

Variable	**q20**	**q40**	**q60**	**q80**
log(Y)	0.231***	0.197***	0.182***	0.168***
	(0.005)	(0.004)	(0.004)	(0.004)
Unemployed	0.0582**	0.0549**	0.0628***	0.0387
	(0.028)	(0.026)	(0.023)	(0.040)
Retired	-0.224***	-0.203***	-0.208***	-0.179***
	(0.017)	(0.018)	(0.016)	(0.017)
Urban	0.077***	0.087***	0.087***	0.079***
	(0.007)	(0.007)	(0.007)	(0.008)
Male	-0.005	-0.004	0.003	0.005
	(0.006)	(0.006)	(0.006)	(0.007)
Married	0.070***	0.059***	0.054***	0.033***
	(0.010)	(0.010)	(0.010)	(0.012)
Age (<30)	0.025	0.046**	0.034*	0.035
	(0.021)	(0.022)	(0.018)	(0.022)
Age (30-50)	0.009	0.014	0.001	0.003
	(0.019)	(0.019)	(0.017)	(0.019)
Age (51-65)	0.031*	0.055***	0.065***	0.072***
	(0.017)	(0.017)	(0.016)	(0.017)
Foreign-born	-0.322***	-0.304***	-0.253***	-0.219***
	(0.011)	(0.017)	(0.015)	(0.016)
Fixed-term contract	-0.048***	-0.063***	-0.052***	-0.069***
	(0.014)	(0.014)	(0.014)	(0.014)
Family size (2)	-0.318***	-0.292***	-0.287***	-0.274***
	(0.013)	(0.014)	(0.014)	(0.017)
Family size (3)	-0.527***	-0.532***	-0.552***	-0.545***
	(0.014)	(0.015)	(0.014)	(0.016)
Family size (4)	-0.664***	-0.667***	-0.699***	-0.714***
	(0.015)	(0.015)	(0.015)	(0.017)
Family size (5+)	-0.854***	-0.885***	-0.879***	-0.889***
	(0.018)	(0.017)	(0.017)	(0.022)
North	0.049***	0.044***	0.022***	0.013
	(0.009)	(0.009)	(0.008)	(0.009)
South	-0.187***	-0.186***	-0.207***	-0.195***
	(0.010)	(0.009)	(0.009)	(0.011)
Constant	7.319***	7.885***	8.290***	8.692***
	(0.049)	(0.048)	(0.041)	(0.045)
Pseudo-R^2	0.2329	0.2258	0.2194	0.2120

Notes: Estimation performed using a conditional quantile regression with 500 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{tot})$ and the quantiles are 5 (quintile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 36,744.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Appendix B2

Further model specifications

Geographical area (macro-region) of residence

Table B2.1: Regression Results for North

Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90
log(Y)	0.249***	0.237***	0.234***	0.233***	0.225***	0.214***	0.201***	0.178***	0.164***
	(0.009)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.008)	(0.006)	(0.009)
Unemployed	0.179***	0.196***	0.227***	0.199***	0.225***	0.177***	0.168***	0.124***	0.122**
	(0.049)	(0.053)	(0.048)	(0.038)	(0.046)	(0.030)	(0.050)	(0.046)	(0.056)
Retired	-0.041**	-0.052***	-0.045***	-0.050***	-0.046***	-0.048***	-0.061***	-0.096***	-0.068***
	(0.017)	(0.017)	(0.014)	(0.015)	(0.014)	(0.017)	(0.017)	(0.019)	(0.022)
Urban	0.079***	0.078***	0.088***	0.092***	0.082***	0.079***	0.064***	0.072***	0.050***
	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)	(0.011)
Male	-0.033***	-0.027***	-0.028***	-0.030***	-0.021***	-0.020***	-0.016**	-0.014*	-0.002
	(0.010)	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)	(0.009)	(0.011)
Married	0.104***	0.104***	0.107***	0.099***	0.078***	0.071***	0.061***	0.065***	0.052***
	(0.014)	(0.010)	(0.010)	(0.012)	(0.011)	(0.011)	(0.013)	(0.012)	(0.015)
Age (<30)	0.134***	0.135***	0.142***	0.128***	0.118***	0.109***	0.086***	0.046*	0.066**
	(0.024)	(0.022)	(0.020)	(0.020)	(0.018)	(0.020)	(0.024)	(0.024)	(0.029)
Age (30-50)	0.130***	0.110***	0.105***	0.087***	0.067***	0.066***	0.048**	0.004	0.046*
	(0.021)	(0.021)	(0.016)	(0.017)	(0.016)	(0.018)	(0.021)	(0.022)	(0.027)
Age (51-65)	0.109***	0.100***	0.104***	0.103***	0.106***	0.116***	0.118***	0.077***	0.099***
	(0.016)	(0.018)	(0.014)	(0.015)	(0.014)	(0.017)	(0.018)	(0.019)	(0.022)
Foreign-born	-0.305***	-0.339***	-0.346***	-0.309***	-0.289***	-0.278***	-0.264***	-0.253***	-0.222***
	(0.018)	(0.016)	(0.014)	(0.016)	(0.014)	(0.013)	(0.016)	(0.016)	(0.019)
Fixed-term contract	0.034*	0.057***	0.053***	0.073***	0.092***	0.101***	0.112***	0.124***	0.121***
	(0.017)	(0.010)	(0.011)	(0.013)	(0.010)	(0.011)	(0.013)	(0.015)	(0.015)
Family size (2)	-0.358***	-0.374***	-0.372***	-0.356***	-0.337***	-0.330***	-0.324***	-0.343***	-0.343***
	(0.016)	(0.014)	(0.013)	(0.015)	(0.013)	(0.012)	(0.015)	(0.017)	(0.021)
Family size (3)	-0.558***	-0.566***	-0.565***	-0.554***	-0.546***	-0.541***	-0.549***	-0.574***	-0.590***
	(0.019)	(0.014)	(0.015)	(0.016)	(0.014)	(0.014)	(0.017)	(0.018)	(0.024)
Family size (4)	-0.694***	-0.695***	-0.697***	-0.681***	-0.676***	-0.698***	-0.715***	-0.757***	-0.787***
	(0.022)	(0.016)	(0.015)	(0.017)	(0.016)	(0.014)	(0.019)	(0.020)	(0.024)
Family size (5+)	-0.911***	-0.897***	-0.886***	-0.861***	-0.856***	-0.854***	-0.871***	-0.905***	-0.910***
	(0.027)	(0.021)	(0.018)	(0.021)	(0.020)	(0.019)	(0.023)	(0.026)	(0.034)
Constant	6.917***	7.229***	7.381***	7.495***	7.685***	7.902***	8.165***	8.593***	8.927***
	(0.089)	(0.074)	(0.058)	(0.075)	(0.065)	(0.066)	(0.079)	(0.066)	(0.089)
Pseudo-R^2	0.2501	0.2350	0.2248	0.2192	0.2164	0.2130	0.2078	0.2037	0.1983

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{North})$ and the quantiles are 10 (decile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4) Sample: N = 24,305.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B2.2: Regression Results for Centre

Variable	**q10**	**q20**	**q30**	**q40**	**q50**	**q60**	**q70**	**q80**	**q90**
log(Y)	0.185***	0.177***	0.172***	0.164***	0.159***	0.160***	0.150***	0.144***	0.131***
	(0.011)	(0.007)	(0.009)	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)	(0.006)
Unemployed	0.086	0.075	0.134**	0.146***	0.121***	0.121***	0.117**	0.067	0.053
	(0.063)	(0.060)	(0.062)	(0.049)	(0.044)	(0.046)	(0.049)	(0.045)	(0.078)
Retired	-0.022	-0.075***	-0.091***	-0.105***	-0.089***	-0.087***	-0.090***	-0.098***	-0.107***
	(0.026)	(0.027)	(0.027)	(0.024)	(0.024)	(0.022)	(0.027)	(0.028)	(0.037)
Urban	0.167***	0.178***	0.184***	0.191***	0.186***	0.188***	0.199***	0.214***	0.204***
	(0.011)	(0.011)	(0.010)	(0.009)	(0.010)	(0.009)	(0.011)	(0.011)	(0.013)
Male	-0.030**	-0.023*	-0.015	-0.012	-0.022**	-0.016*	-0.019*	-0.005	-0.004
	(0.012)	(0.012)	(0.011)	(0.010)	(0.010)	(0.009)	(0.011)	(0.011)	(0.012)
Married	0.082***	0.071***	0.049***	0.053***	0.066***	0.042***	0.047***	0.070***	0.033
	(0.017)	(0.016)	(0.015)	(0.014)	(0.015)	(0.014)	(0.017)	(0.018)	(0.021)
Age (<30)	0.146***	0.083**	0.044	0.024	0.042	0.043	0.032	0.042	-0.026
	(0.036)	(0.033)	(0.033)	(0.027)	(0.028)	(0.026)	(0.028)	(0.035)	(0.043)
Age (30-50)	0.125***	0.047	0.029	0.006	0.022	0.039	0.021	0.004	-0.038
	(0.031)	(0.031)	(0.029)	(0.026)	(0.026)	(0.024)	(0.029)	(0.031)	(0.039)
Age (51-65)	0.124***	0.077***	0.066**	0.052**	0.051**	0.072***	0.071***	0.050*	0.031
	(0.026)	(0.026)	(0.027)	(0.023)	(0.022)	(0.020)	(0.026)	(0.028)	(0.035)
Foreign-born	-0.299***	-0.292***	-0.311***	-0.312***	-0.284***	-0.300***	-0.292***	-0.286***	-0.282***
	(0.024)	(0.020)	(0.017)	(0.021)	(0.018)	(0.020)	(0.022)	(0.020)	(0.024)
Fixed-term contract	0.037**	0.050***	0.065***	0.081***	0.080***	0.081***	0.111***	0.107***	0.082***
	(0.018)	(0.016)	(0.018)	(0.014)	(0.017)	(0.015)	(0.019)	(0.017)	(0.021)
Family size (2)	-0.410***	-0.363***	-0.351***	-0.344***	-0.345***	-0.325***	-0.341***	-0.369***	-0.323***
	(0.023)	(0.022)	(0.019)	(0.018)	(0.020)	(0.018)	(0.022)	(0.024)	(0.028)
Family size (3)	-0.615***	-0.581***	-0.555***	-0.568***	-0.575***	-0.565***	-0.582***	-0.601***	-0.582***
	(0.026)	(0.022)	(0.022)	(0.018)	(0.021)	(0.019)	(0.024)	(0.024)	(0.026)
Family size (4)	-0.811***	-0.783***	-0.762***	-0.756***	-0.745***	-0.728***	-0.719***	-0.747***	-0.722***
	(0.028)	(0.023)	(0.023)	(0.021)	(0.023)	(0.020)	(0.025)	(0.026)	(0.028)
Family size (5+)	-1.072***	-0.959***	-0.917***	-0.937***	-0.960***	-0.933***	-0.937***	-0.938***	-0.841***
	(0.034)	(0.027)	(0.029)	(0.023)	(0.028)	(0.027)	(0.028)	(0.035)	(0.039)
constant	7.529***	7.799***	7.976***	8.181***	8.323***	8.403***	8.619***	8.829***	9.190***
	(0.112)	(0.075)	(0.091)	(0.065)	(0.068)	(0.077)	(0.075)	(0.077)	(0.074)
Pseudo-R^2	0.2675	0.2545	0.2464	0.2389	0.2317	0.2260	0.2177	0.2096	0.2073

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{Centre})$, regional variables omitted, and the quantiles are 10 (decile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 12,557.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B2.3: Regression Results for South and Islands

Variable	**q10**	**q20**	**q30**	**q40**	**q50**	**q60**	**q70**	**q80**	**q90**
log(Y)	0.171***	0.168***	0.167***	0.165***	0.163***	0.164***	0.154***	0.147***	0.146***
	(0.008)	(0.007)	(0.006)	(0.005)	(0.007)	(0.006)	(0.007)	(0.007)	(0.005)
Unemployed	0.083**	0.029	0.003	0.035	0.049	0.041	0.029	0.043	0.136**
	(0.040)	(0.024)	(0.038)	(0.040)	(0.035)	(0.032)	(0.039)	(0.048)	(0.060)
Retired	-0.158***	-0.151***	-0.135***	-0.121***	-0.134***	-0.138***	-0.136***	-0.134***	-0.143***
	(0.029)	(0.024)	(0.022)	(0.018)	(0.022)	(0.025)	(0.022)	(0.027)	(0.026)
Urban	0.017	0.054***	0.057***	0.047***	0.032***	0.024**	0.016	0.029**	0.035**
	(0.014)	(0.011)	(0.010)	(0.009)	(0.010)	(0.011)	(0.011)	(0.013)	(0.016)
Male	0.018	0.008	0.002	0.004	0.004	0.003	-0.003	-0.015	-0.013
	(0.013)	(0.011)	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)	(0.012)	(0.014)
Married	0.082***	0.101***	0.090***	0.104***	0.110***	0.083***	0.081***	0.059***	0.060***
	(0.019)	(0.016)	(0.015)	(0.014)	(0.016)	(0.017)	(0.016)	(0.019)	(0.021)
Age (<30)	0.112***	0.119***	0.133***	0.150***	0.148***	0.129***	0.131***	0.134***	0.109***
	(0.033)	(0.028)	(0.026)	(0.024)	(0.028)	(0.032)	(0.030)	(0.032)	(0.038)
Age (30-50)	0.104***	0.081***	0.097***	0.097***	0.083***	0.090***	0.094***	0.097***	0.053
	(0.030)	(0.026)	(0.025)	(0.022)	(0.026)	(0.028)	(0.025)	(0.028)	(0.033)
Age (51-65)	0.060**	0.067***	0.072***	0.067***	0.053**	0.049*	0.056***	0.065***	0.028
	(0.028)	(0.022)	(0.022)	(0.017)	(0.021)	(0.025)	(0.022)	(0.025)	(0.028)
Foreign-born	-0.279***	-0.274***	-0.244***	-0.229***	-0.224***	-0.203***	-0.170***	-0.166***	-0.172***
	(0.038)	(0.026)	(0.027)	(0.027)	(0.029)	(0.031)	(0.029)	(0.028)	(0.056)
Fixed-term contract	-0.002	0.012	0.026*	0.033*	0.047***	0.058***	0.073***	0.102***	0.068***
	(0.022)	(0.020)	(0.015)	(0.019)	(0.018)	(0.018)	(0.022)	(0.025)	(0.022)
Family size (2)	-0.377***	-0.402***	-0.382***	-0.393***	-0.393***	-0.375***	-0.394***	-0.401***	-0.405***
	(0.026)	(0.022)	(0.019)	(0.019)	(0.020)	(0.023)	(0.022)	(0.024)	(0.027)
Family size (3)	-0.626***	-0.664***	-0.655***	-0.652***	-0.651***	-0.635***	-0.649***	-0.646***	-0.659***
	(0.026)	(0.023)	(0.021)	(0.021)	(0.024)	(0.028)	(0.025)	(0.026)	(0.029)
Family size (4)	-0.778***	-0.807***	-0.798***	-0.800***	-0.784***	-0.757***	-0.792***	-0.811***	-0.805***
	(0.030)	(0.025)	(0.023)	(0.021)	(0.026)	(0.028)	(0.025)	(0.028)	(0.032)
Family size (5+)	-1.019***	-1.011***	-1.007***	-1.008***	-0.974***	-0.944***	-1.015***	-0.986***	-0.988***
	(0.033)	(0.028)	(0.026)	(0.029)	(0.029)	(0.031)	(0.029)	(0.033)	(0.039)
Constant	7.487***	7.721***	7.853***	7.982***	8.127***	8.238***	8.495***	8.734***	8.992
	(-0.079)	(-0.067)	(-0.061)	(-0.055)	(-0.071)	(-0.065)	(-0.075)	(-0.064)	(-0.063)
Pseudo-R^2	0.1775	0.1742	0.1705	0.1658	0.1625	0.1594	0.1586	0.1601	0.1648

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{South})$, regional variables omitted, and the quantiles are 10 (decile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 16,461.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Size of the location of residence

Table B2.4: Regression Results for Urban environment

Variable	**q10**	**q20**	**q30**	**q40**	**q50**	**q60**	**q70**	**q80**	**q90**
log(Y)	0.272***	0.257***	0.249***	0.245***	0.234***	0.223***	0.203***	0.181***	0.159***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)	(0.006)	(0.005)
Unemployed	0.151***	0.141***	0.115***	0.164***	0.120***	0.171***	0.124***	0.124***	0.075*
	(0.032)	(0.038)	(0.036)	(0.048)	(0.031)	(0.053)	(0.039)	(0.035)	(0.045)
Retired	-0.077***	-0.074***	-0.061***	-0.056***	-0.067***	-0.074***	-0.080***	-0.084***	-0.091***
	(0.028)	(0.015)	(0.018)	(0.015)	(0.019)	(0.018)	(0.021)	(0.021)	(0.027)
Male	-0.038***	-0.025***	-0.031***	-0.026***	-0.022***	-0.023***	-0.019**	-0.013	-0.007
	(0.011)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)
Married	0.088***	0.089***	0.090***	0.081***	0.076***	0.062***	0.057***	0.053***	0.062***
	(0.015)	(0.009)	(0.013)	(0.012)	(0.011)	(0.010)	(0.011)	(0.013)	(0.017)
Age (<30)	0.141***	0.128***	0.137***	0.126***	0.111***	0.074***	0.064***	0.052*	0.072**
	(0.032)	(0.019)	(0.021)	(0.022)	(0.022)	(0.021)	(0.023)	(0.027)	(0.034)
Age (30-50)	0.134***	0.114***	0.106***	0.091***	0.069***	0.049***	0.035*	0.018	0.020
	(0.030)	(0.017)	(0.020)	(0.018)	(0.020)	(0.018)	(0.021)	(0.023)	(0.029)
Age (51-65)	0.081***	0.064***	0.075***	0.073***	0.075***	0.066***	0.076***	0.067***	0.071***
	(0.028)	(0.016)	(0.018)	(0.015)	(0.018)	(0.016)	(0.020)	(0.021)	(0.026)
Foreign-born	-0.232***	-0.271***	-0.283***	-0.252***	-0.254***	-0.254***	-0.238***	-0.244***	-0.224***
	(0.020)	(0.013)	(0.015)	(0.018)	(0.014)	(0.014)	(0.016)	(0.017)	(0.020)
Fixed-term contract	0.053***	0.083***	0.084***	0.089***	0.111***	0.126***	0.134***	0.158***	0.125***
	(0.017)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.015)	(0.013)
Family size (2)	-0.363***	-0.370***	-0.371***	-0.354***	-0.350***	-0.332***	-0.337***	-0.354***	-0.343***
	(0.019)	(0.014)	(0.015)	(0.014)	(0.014)	(0.013)	(0.016)	(0.018)	(0.023)
Family size (3)	-0.586***	-0.575***	-0.581***	-0.572***	-0.577***	-0.568***	-0.579***	-0.602***	-0.604***
	(0.021)	(0.015)	(0.017)	(0.015)	(0.016)	(0.016)	(0.016)	(0.020)	(0.022)
Family size (4)	-0.764***	-0.753***	-0.755***	-0.734***	-0.730***	-0.718***	-0.748***	-0.780***	-0.815***
	(0.021)	(0.016)	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.022)	(0.025)
Family size (5+)	-0.985***	-0.988***	-0.960***	-0.919***	-0.915***	-0.906***	-0.915***	-0.900***	-0.864***
	(0.032)	(0.022)	(0.019)	(0.022)	(0.020)	(0.020)	(0.019)	(0.025)	(0.032)
Constant	6.736***	7.076***	7.290***	7.435***	7.668***	7.897***	8.227***	8.614***	9.036***
	(0.080)	(0.061)	(0.058)	(0.059)	(0.064)	(0.055)	(0.068)	(0.067)	(0.055)
Pseudo-R^2	0.2636	0.2554	0.2456	0.2372	0.2315	0.2260	0.2192	0.2141	0.2082

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{urban})$, regional variables omitted, and the quantiles are 10 (decile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 24,143.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B2.5: Regression Results for Rural environment

Variable	**q10**	**q20**	**q30**	**q40**	**q50**	**q60**	**q70**	**q80**	**q90**
log(Y)	0.223***	0.218***	0.218***	0.212***	0.201***	0.195***	0.185***	0.174***	0.163***
	(-0.007)	(-0.006)	(-0.005)	(-0.005)	(-0.007)	(-0.005)	(-0.006)	(-0.005)	(-0.006)
Unemployed	0.064**	0.033	0.073*	0.108***	0.090***	0.073**	0.071*	0.074*	0.121**
	(-0.032)	(-0.028)	(-0.044)	(-0.034)	(-0.031)	(-0.031)	(-0.040)	(-0.039)	(-0.051)
Retired	-0.078***	-0.077***	-0.079***	-0.077***	-0.071***	-0.062***	-0.073***	-0.069***	-0.089***
	(-0.019)	(-0.019)	(-0.017)	(-0.015)	(-0.018)	(-0.016)	(-0.017)	(-0.017)	(-0.023)
Male	-0.021**	-0.019**	-0.017**	-0.022***	-0.021***	-0.021***	-0.023***	-0.022***	-0.011
	(-0.009)	(-0.008)	(-0.007)	(-0.007)	(-0.007)	(-0.006)	(-0.008)	(-0.008)	(-0.011)
Married	0.088***	0.072***	0.074***	0.068***	0.062***	0.049***	0.048***	0.044***	0.033*
	(-0.013)	(-0.012)	(-0.009)	(-0.010)	(-0.012)	(-0.010)	(-0.012)	(-0.013)	(-0.018)
Age (<30)	0.192***	0.177***	0.167***	0.158***	0.157***	0.158***	0.143***	0.120***	0.0756**
	(-0.026)	(-0.023)	(-0.019)	(-0.019)	(-0.021)	(-0.019)	(-0.020)	(-0.022)	(-0.032)
Age (30-50)	0.145***	0.142***	0.124***	0.120***	0.118***	0.114***	0.109***	0.092***	0.049*
	(-0.022)	(-0.021)	(-0.019)	(-0.016)	(-0.018)	(-0.017)	(-0.019)	(-0.021)	(-0.026)
Age (51-65)	0.138***	0.139***	0.128***	0.123***	0.128***	0.137***	0.136***	0.113***	0.093***
	(-0.019)	(-0.019)	(-0.017)	(-0.015)	(-0.017)	(-0.015)	(-0.016)	(-0.018)	(-0.024)
Foreign-born	-0.230***	-0.222***	-0.242***	-0.239***	-0.227***	-0.210***	-0.210***	-0.204***	-0.184***
	(-0.020)	(-0.014)	(-0.014)	(-0.015)	(-0.015)	(-0.017)	(-0.018)	(-0.018)	(-0.025)
Fixed-term contract	0.002	0.004	0.030**	0.036***	0.061***	0.067***	0.080***	0.094***	0.067***
	(-0.013)	(-0.014)	(-0.013)	(-0.012)	(-0.012)	(-0.012)	(-0.014)	(-0.011)	(-0.016)
Family size (2)	-0.373***	-0.354***	-0.362***	-0.345***	-0.337***	-0.340***	-0.340***	-0.347***	-0.336***
	(-0.018)	(-0.015)	(-0.012)	(-0.013)	(-0.016)	(-0.014)	(-0.016)	(-0.017)	(-0.026)
Family size (3)	-0.641***	-0.619***	-0.594***	-0.572***	-0.567***	-0.565***	-0.574***	-0.573***	-0.599***
	(-0.019)	(-0.017)	(-0.013)	(-0.014)	(-0.016)	(-0.016)	(-0.017)	(-0.018)	(-0.026)
Family size (4)	-0.774***	-0.771***	-0.752***	-0.723***	-0.710***	-0.720***	-0.734***	-0.740***	-0.742***
	(-0.021)	(-0.017)	(-0.013)	(-0.014)	(-0.016)	(-0.015)	(-0.018)	(-0.019)	(-0.028)
Family size (5+)	-0.970***	-0.945***	-0.912***	-0.894***	-0.879***	-0.888***	-0.918***	-0.934***	-0.942***
	(-0.026)	(-0.021)	(-0.019)	(-0.016)	(-0.021)	(-0.017)	(-0.020)	(-0.021)	(-0.033)
constant	7.085***	7.319***	7.449***	7.621***	7.828***	8.003***	8.244***	8.518***	8.875***
	(-0.074)	(-0.060)	(-0.054)	(-0.050)	(-0.066)	(-0.050)	(-0.058)	(-0.055)	(-0.067)
Pseudo-R^2	0.2059	0.1989	0.1932	0.1881	0.1842	0.1829	0.1809	0.1783	0.1770

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{rural})$, regional variables omitted, and the quantiles are 10 (decile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 29,180.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Disaggregation of consumption categories over time

Services	2018	2019	2020	2021	2022
q20	0.178***	0.194***	0.153***	0.168***	0.189***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.003)
q40	0.158***	0.174***	0.141***	0.164***	0.184***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
q60	0.150***	0.161***	0.133***	0.157***	0.176***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
q80	0.145***	0.141***	0.130***	0.152***	0.164***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)

Table B2.6: Regression results for Services (2018-2022).

Nondurables	2018	2019	2020	2021	2022
q20	0.102***	0.125***	0.098***	0.114***	0.097***
	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)
q40	0.092***	0.098***	0.086***	0.110***	0.093***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
q60	0.088***	0.078***	0.084***	0.099***	0.075***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
q80	0.078***	0.074***	0.078***	0.088***	0.071***
	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)

Table B2.7: Regression results for Nondurables (2018-2022).

Durables	2018	2019	2020	2021	2022
q20	0.348***	0.357***	0.286***	0.293***	0.240***
	(0.011)	(0.008)	(0.009)	(0.008)	(0.011)
q40	0.280***	0.296***	0.243***	0.273***	0.234***
	(0.007)	(0.009)	(0.007)	(0.006)	(0.007)
q60	0.249***	0.248***	0.224***	0.240***	0.225***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
q80	0.241***	0.216***	0.222***	0.223***	0.203***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)

Table B2.8: Regression results for Durables (2018-2022).

Appendix B3

Robustness checks

Table B3.1: Decile regression results: inclusion of liquid and illiquid wealth (ISEE)

Variable	**q10**	**q20**	**q30**	**q40**	**q50**	**q60**	**q70**	**q80**	**q90**
logY	0.138***	0.140***	0.128***	0.137***	0.125***	0.120***	0.110***	0.107***	0.095***
	(0.009)	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Liquid wealth	0.029***	0.032***	0.040***	0.036***	0.042***	0.041***	0.040***	0.038***	0.039***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Fixed assets	0.078***	0.073***	0.074***	0.064***	0.057***	0.056***	0.050***	0.056***	0.053***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)
Unemployment	0.066**	0.002	0.087*	0.114***	0.055*	0.030	0.004	0.038	-0.013
	(0.027)	(0.044)	(0.051)	(0.033)	(0.028)	(0.033)	(0.043)	(0.051)	(0.065)
Retired	-0.111**	-0.144***	-0.165***	-0.185***	-0.178***	-0.146***	-0.133***	-0.100***	-0.049
	(0.045)	(0.038)	(0.028)	(0.023)	(0.026)	(0.027)	(0.037)	(0.035)	(0.042)
Urban	0.102***	0.081***	0.093***	0.081***	0.085***	0.074***	0.070***	0.052***	0.073***
	(0.012)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.010)	(0.011)	(0.014)
Male	0.008	0.003	0.004	0.004	0.002	0.000	-0.001	0.003	0.002
	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.009)	(0.010)	(0.012)
Married	0.034*	0.042***	0.028**	0.024**	0.030**	0.016	0.011	-0.010	0.004
	(0.019)	(0.015)	(0.014)	(0.012)	(0.015)	(0.012)	(0.017)	(0.017)	(0.024)
Age(<30)	0.106**	0.110***	0.048	0.028	0.036	0.052*	0.059	0.074*	0.110**
	(0.049)	(0.041)	(0.031)	(0.029)	(0.031)	(0.029)	(0.042)	(0.039)	(0.050)
Age(30–50)	0.095**	0.084**	0.039	0.019	0.008	0.036	0.048	0.081**	0.095**
	(0.046)	(0.039)	(0.030)	(0.029)	(0.027)	(0.028)	(0.039)	(0.039)	(0.047)
Age(51–65)	0.100**	0.099***	0.053*	0.026	0.029	0.050*	0.076**	0.093**	0.114**
	(0.044)	(0.037)	(0.028)	(0.027)	(0.027)	(0.028)	(0.038)	(0.038)	(0.046)
Foreign	-0.238***	-0.256***	-0.222***	-0.168***	-0.123***	-0.110***	-0.114***	-0.090***	-0.091**
	(0.021)	(0.024)	(0.035)	(0.021)	(0.024)	(0.020)	(0.019)	(0.026)	(0.036)
Fixed-term	-0.050**	0.005	0.022	0.043***	0.046***	0.063***	0.073***	0.084***	0.023
	(0.020)	(0.016)	(0.014)	(0.014)	(0.012)	(0.013)	(0.016)	(0.015)	(0.017)
Family size (2)	-0.442***	-0.442***	-0.433***	-0.398***	-0.432***	-0.419***	-0.423***	-0.424***	-0.412***
	(0.033)	(0.027)	(0.028)	(0.026)	(0.027)	(0.026)	(0.032)	(0.041)	(0.045)
Family size (3)	-0.681***	-0.683***	-0.671***	-0.646***	-0.664***	-0.664***	-0.661***	-0.657***	-0.687***
	(0.033)	(0.027)	(0.026)	(0.025)	(0.028)	(0.023)	(0.033)	(0.039)	(0.044)
Family size (4)	-0.868***	-0.874***	-0.857***	-0.814***	-0.831***	-0.827***	-0.831***	-0.825***	-0.852***
	(0.032)	(0.027)	(0.027)	(0.026)	(0.028)	(0.024)	(0.032)	(0.039)	(0.044)
Large family (5+)	-1.034***	-1.012***	-0.972***	-0.940***	-0.962***	-0.977***	-0.953***	-0.960***	-0.944***
	(0.036)	(0.029)	(0.028)	(0.026)	(0.029)	(0.026)	(0.033)	(0.041)	(0.053)
North	0.030**	0.044***	0.052***	0.044***	0.044***	0.038***	0.028**	0.004	-0.018
	(0.015)	(0.011)	(0.012)	(0.011)	(0.012)	(0.009)	(0.014)	(0.014)	(0.016)
South	-0.206***	-0.166***	-0.160***	-0.160***	-0.124***	-0.105***	-0.095***	-0.099***	-0.087***
	(0.015)	(0.012)	(0.012)	(0.012)	(0.013)	(0.011)	(0.016)	(0.016)	(0.019)
constant	6.967***	7.136***	7.316***	7.494***	7.727***	7.867***	8.141***	8.263***	8.574***
	(0.120)	(0.098)	(0.087)	(0.090)	(0.075)	(0.084)	(0.092)	(0.097)	(0.123)
Pseudo-R^2	0.189	0.186	0.180	0.174	0.168	0.161	0.155	0.155	0.152

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{tot})$ and the variables *Liquid Wealth* and *Fixed Assets* are added. They regard the log of moveable assets (*patrimonio mobiliare*) and fixed assets (*patrimonio immobiliare*), with no collinearity with $log(Y)$. The quantiles are 10 (decile), the interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 23,007.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B3.2: Decile regression results: inclusion of liquid wealth and home-ownership

Variable	**q10**	**q20**	**q30**	**q40**	**q50**	**q60**	**q70**	**q80**	**q90**
logY	0.128***	0.136***	0.127***	0.127***	0.123***	0.118***	0.109***	0.100***	0.103***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
logISEE	0.047***	0.047***	0.048***	0.047***	0.047***	0.048***	0.047***	0.044***	0.045***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Unemployment	0.058**	0.071**	0.055**	0.065**	0.034	0.019	0.004	-0.002	0.050
	(0.028)	(0.031)	(0.025)	(0.029)	(0.024)	(0.030)	(0.031)	(0.036)	(0.062)
Retired	-0.136***	-0.153***	-0.140***	-0.138***	-0.148***	-0.139***	-0.112***	-0.089***	-0.093***
	(0.036)	(0.027)	(0.024)	(0.021)	(0.026)	(0.025)	(0.026)	(0.034)	(0.034)
Urban	0.079***	0.082***	0.081***	0.080***	0.076***	0.064***	0.054***	0.053***	0.056***
	(0.010)	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)	(0.012)
Male	0.001	0.005	0.007	0.006	-0.001	-0.002	0.000	0.002	0.001
	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)	(0.010)
Married	0.058***	0.047***	0.031**	0.027**	0.011	0.017	-0.001	-0.005	0.014
	(0.017)	(0.013)	(0.012)	(0.011)	(0.010)	(0.011)	(0.012)	(0.013)	(0.019)
Age(<30)	0.114***	0.093***	0.088***	0.080***	0.045*	0.054**	0.065**	0.090**	0.096***
	(0.044)	(0.031)	(0.026)	(0.025)	(0.027)	(0.025)	(0.029)	(0.035)	(0.035)
Age(30–50)	0.105***	0.080***	0.086***	0.079***	0.047*	0.049**	0.074***	0.100***	0.082**
	(0.040)	(0.029)	(0.024)	(0.024)	(0.026)	(0.024)	(0.027)	(0.034)	(0.032)
Age(51–65)	0.095**	0.070**	0.083***	0.074***	0.048*	0.053**	0.074***	0.101***	0.100***
	(0.037)	(0.028)	(0.024)	(0.022)	(0.025)	(0.024)	(0.026)	(0.034)	(0.032)
Foreign	-0.208***	-0.197***	-0.188***	-0.184***	-0.167***	-0.170***	-0.147***	-0.155***	-0.130***
	(0.016)	(0.013)	(0.015)	(0.015)	(0.012)	(0.014)	(0.013)	(0.016)	(0.023)
Fixed-term	0.008	0.025**	0.039***	0.062***	0.056***	0.061***	0.084***	0.097***	0.062***
	(0.016)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.013)	(0.015)
Family size (2)	-0.416***	-0.410***	-0.413***	-0.410***	-0.403***	-0.415***	-0.415***	-0.421***	-0.388***
	(0.026)	(0.021)	(0.019)	(0.020)	(0.018)	(0.021)	(0.024)	(0.025)	(0.037)
Family size (3)	-0.674***	-0.661***	-0.657***	-0.642***	-0.619***	-0.637***	-0.626***	-0.629***	-0.608***
	(0.027)	(0.020)	(0.019)	(0.019)	(0.017)	(0.020)	(0.024)	(0.024)	(0.032)
Family size (4)	-0.852***	-0.840***	-0.839***	-0.817***	-0.792***	-0.802***	-0.811***	-0.805***	-0.793***
	(0.029)	(0.021)	(0.019)	(0.020)	(0.018)	(0.020)	(0.024)	(0.024)	(0.033)
Large family (5+)	-1.078***	-1.032***	-1.000***	-0.989***	-0.959***	-0.958***	-0.975***	-0.960***	-0.974***
	(0.032)	(0.022)	(0.019)	(0.021)	(0.019)	(0.022)	(0.024)	(0.027)	(0.035)
North	0.037***	0.033***	0.035***	0.024**	0.022***	0.028***	0.033***	0.010	-0.004
	(0.014)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.011)	(0.014)
South	-0.228***	-0.195***	-0.199***	-0.187***	-0.169***	-0.139***	-0.116***	-0.130***	-0.108***
	(0.014)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.012)	(0.015)
Home-ownership	0.159***	0.173***	0.191***	0.190***	0.192***	0.183***	0.191***	0.199***	0.167***
	(0.012)	(0.008)	(0.009)	(0.010)	(0.009)	(0.008)	(0.009)	(0.011)	(0.014)
constant	7.611***	7.686***	7.866***	7.979***	8.145***	8.285***	8.463***	8.688***	8.853***
	(0.079)	(0.057)	(0.057)	(0.056)	(0.051)	(0.050)	(0.053)	(0.065)	(0.070)
Pseudo-R^2	0.243	0.240	0.231	0.223	0.216	0.207	0.198	0.190	0.179

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{tot})$ and the variables $Liquid\ Wealth$ and $Home-ownership$ are added. They regard the log of moveable assets (*patrimonio mobiliare*), with no collinearity with $log(Y)$ and a dummy for house propriety. The quantiles are 10 (decile), the interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 23,007.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B3.3: Unconditional Quantile Regression results

Variable	**q20**	**q40**	**q60**	**q80**
log(Y)	0.172***	0.168***	0.156***	0.156***
	(0.009)	(0.009)	(0.014)	(0.022)
Unemployed	0.064	0.107***	0.109***	0.118***
	(0.038)	(0.018)	(0.017)	(0.021)
Retired	-0.074**	-0.052*	-0.062**	-0.089***
	(0.018)	(0.019)	(0.016)	(0.013)
Urban	0.058	0.095**	0.115**	0.117**
	(0.036)	(0.030)	(0.032)	(0.035)
Male	-0.011	-0.024***	-0.024**	-0.014
	(0.008)	(0.005)	(0.007)	(0.007)
Married	0.058*	0.081***	0.084***	0.084**
	(0.025)	(0.012)	(0.016)	(0.021)
Age (<30)	0.052	0.120***	0.137***	0.138***
	(0.040)	(0.020)	(0.015)	(0.023)
Age (30-50)	0.033	0.086***	0.100***	0.099***
	(0.021)	(0.014)	(0.013)	(0.017)
Age (51-65)	0.050**	0.090***	0.109***	0.123**
	(0.012)	(0.009)	(0.012)	(0.028)
Foreign-born	-0.385***	-0.287***	-0.255***	-0.180***
	(0.023)	(0.023)	(0.024)	(0.019)
Fixed-term contract	0.064***	0.078***	0.077**	0.053**
	(0.012)	(0.012)	(0.023)	(0.016)
Family size (2)	-0.146**	-0.278***	-0.397***	-0.529***
	(0.052)	(0.031)	(0.018)	(0.032)
Family size (3)	-0.354**	-0.503***	-0.675***	-0.816***
	(0.098)	(0.058)	(0.020)	(0.061)
Family size (4)	-0.553***	-0.687***	-0.837***	-0.929***
	(0.116)	(0.050)	(0.025)	(0.086)
Family size (5+)	-0.920***	-0.864***	-0.912***	-0.916***
	(0.110)	(0.037)	(0.036)	(0.072)
Constant	7.582***	7.987***	8.482***	8.912***
	(0.064)	(0.115)	(0.142)	(0.186)
R^2	0.183	0.219	0.220	0.182
AIC	119466.4	100128.9	103466.4	117381.8

Notes: Estimates performed using an unconditional quantile regression (Firpo et al., 2009) with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{tot})$ and the quantiles are 5 (quintile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 53,310.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B3.4: Decile regression results: inclusion of quadratic term.

Variable	**q10**	**q20**	**q30**	**q40**	**q50**	**q60**	**q70**	**q80**	**q90**
log(Y)	-0.458***	-0.493***	-0.499***	-0.555***	-0.606***	-0.646***	-0.717***	-0.679***	-0.724***
	(0.031)	(0.030)	(0.030)	(0.029)	(0.032)	(0.030)	(0.035)	(0.038)	(0.054)
$(\log Y)^2$	0.036***	0.038***	0.038***	0.042***	0.044***	0.046***	0.050***	0.047***	0.049***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Unemployment	0.077***	0.049**	0.043*	0.066**	0.067**	0.083***	0.068***	0.054	0.051
	(0.021)	(0.021)	(0.024)	(0.027)	(0.026)	(0.021)	(0.025)	(0.034)	(0.031)
Retired	-0.066***	-0.084***	-0.083***	-0.084***	-0.076***	-0.079***	-0.079***	-0.092***	-0.097***
	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.013)	(0.015)
Urban	0.085***	0.085***	0.095***	0.090***	0.082***	0.080***	0.069***	0.074***	0.066***
	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
Male	-0.024***	-0.023***	-0.025***	-0.021***	-0.020***	-0.017***	-0.014**	-0.016***	-0.011
	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
Married	0.102***	0.096***	0.088***	0.084***	0.079***	0.064***	0.056***	0.054***	0.045***
	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.010)
Age(<30)	0.132***	0.126***	0.121***	0.108***	0.120***	0.103***	0.101***	0.086***	0.073***
	(0.017)	(0.016)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.018)	(0.021)
Age(30–50)	0.121***	0.093***	0.085***	0.075***	0.073***	0.067***	0.069***	0.056***	0.045**
	(0.015)	(0.014)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.015)	(0.018)
Age(51–65)	0.099***	0.088***	0.083***	0.076***	0.085***	0.082***	0.092***	0.075***	0.067***
	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.013)	(0.016)
Foreign	-0.302***	-0.315***	-0.316***	-0.299***	-0.278***	-0.260***	-0.247***	-0.240***	-0.219***
	(0.014)	(0.010)	(0.011)	(0.011)	(0.010)	(0.009)	(0.012)	(0.011)	(0.013)
Fixed-term	0.027***	0.043***	0.045***	0.061***	0.076***	0.080***	0.095***	0.098***	0.089***
	(0.010)	(0.008)	(0.008)	(0.008)	(0.007)	(0.009)	(0.008)	(0.011)	(0.009)
Family size (2)	-0.370***	-0.370***	-0.360***	-0.349***	-0.339***	-0.325***	-0.328***	-0.333***	-0.328***
	(0.012)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.012)	(0.015)
Family size (3)	-0.579***	-0.585***	-0.574***	-0.561***	-0.554***	-0.544***	-0.544***	-0.557***	-0.565***
	(0.013)	(0.010)	(0.011)	(0.009)	(0.010)	(0.011)	(0.011)	(0.013)	(0.016)
Family size (4)	-0.738***	-0.732***	-0.726***	-0.698***	-0.689***	-0.683***	-0.693***	-0.709***	-0.726***
	(0.014)	(0.011)	(0.012)	(0.010)	(0.011)	(0.011)	(0.011)	(0.014)	(0.017)
Large family (5+)	-0.975***	-0.933***	-0.918***	-0.893***	-0.880***	-0.865***	-0.867***	-0.881***	-0.859***
	(0.017)	(0.014)	(0.014)	(0.012)	(0.014)	(0.013)	(0.014)	(0.016)	(0.022)
North	0.031***	0.033***	0.041***	0.043***	0.040***	0.037***	0.039***	0.045***	0.035***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.009)
South	-0.256***	-0.240***	-0.219***	-0.216***	-0.203***	-0.186***	-0.164***	-0.142***	-0.143***
	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)	(0.010)
constant	10.350***	10.700***	10.840***	11.200***	11.540***	11.840***	12.300***	12.330***	12.820***
	(0.137)	(0.138)	(0.137)	(0.129)	(0.146)	(0.133)	(0.158)	(0.174)	(0.244)
Pseudo-R^2	0.269	0.262	0.255	0.247	0.242	0.237	0.231	0.224	0.218

Notes: Estimation performed using a conditional quantile regression with 1000 bootstrap replications. Standard errors are reported in parentheses. The dependent variable is $log(C_{tot})$ and the variable $(logY)^2$ is added. It regards the square of the log of income $log(Y)$. The quantiles are 10 (decile), the interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 53,310.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B3.5: Quintile Results excluding income from retired people.

Variable	**q20**	**q40**	**q60**	**q80**
log(Y)	0.189***	0.175***	0.170***	0.142***
	(0.005)	(0.004)	(0.004)	(0.004)
Unemployed	0.081***	0.090***	0.090***	0.066**
	(0.021)	(0.022)	(0.020)	(0.030)
Urban	0.085***	0.086***	0.080***	0.082***
	(0.006)	(0.006)	(0.006)	(0.007)
Male	-0.004	-0.004	-0.005	-0.005
	(0.006)	(0.005)	(0.005)	(0.007)
Married	0.093***	0.081***	0.052***	0.052***
	(0.008)	(0.008)	(0.008)	(0.011)
Age (<30)	0.057***	0.037*	0.004	-0.001
	(0.021)	(0.019)	(0.020)	(0.024)
Age (30-50)	0.035*	0.015	-0.014	-0.028
	(0.020)	(0.018)	(0.019)	(0.022)
Age (51-65)	0.027	0.018	0.003	0.005
	(0.021)	(0.018)	(0.019)	(0.023)
Foreign-born	-0.343***	-0.327***	-0.294***	-0.272***
	(0.011)	(0.011)	(0.009)	(0.014)
Fixed-term contract	0.042***	0.061***	0.083***	0.107***
	(0.010)	(0.009)	(0.007)	(0.011)
Family size (2)	-0.382***	-0.369***	-0.348***	-0.386***
	(0.014)	(0.011)	(0.012)	(0.017)
Family size (3)	-0.599***	-0.581***	-0.569***	-0.614***
	(0.013)	(0.011)	(0.012)	(0.017)
Family size (4)	-0.752***	-0.727***	-0.715***	-0.779***
	(0.014)	(0.012)	(0.013)	(0.018)
Family size (5+)	-0.952***	-0.926***	-0.894***	-0.951***
	(0.016)	(0.013)	(0.014)	(0.020)
North	0.041***	0.046***	0.036***	0.035***
	(0.008)	(0.007)	(0.007)	(0.009)
South	-0.226***	-0.213***	-0.177***	-0.143***
	(0.009)	(0.008)	(0.009)	(0.012)
Constant	7.753***	8.123***	8.407***	8.988***
	(0.051)	(0.044)	(0.041)	(0.049)
Pseudo-R^2	0.2512	0.2385	0.2266	0.2179

Notes: Estimation performed using a conditional quantile regression with 500 bootstrap replications, excluding people in retirement. Standard errors are reported in parentheses. The dependent variable is $log(C_{unretired})$ and the quantiles are 5 (quintile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 53,310.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B3.6: Quintile Results excluding people under 18.

Variable	**q20**	**q40**	**q60**	**q80**
log(Y)	0.179***	0.172***	0.169***	0.153***
	(0.004)	(0.004)	(0.004)	(0.005)
Unemployed	0.072***	0.075***	0.093***	0.091***
	(0.021)	(0.021)	(0.021)	(0.032)
Retired	-0.081***	-0.070***	-0.081***	-0.102***
	(0.012)	(0.011)	(0.011)	(0.012)
Urban	0.104***	0.106***	0.102***	0.101***
	(0.005)	(0.005)	(0.005)	(0.007)
Male	-0.025***	-0.022***	-0.019***	-0.013*
	(0.006)	(0.006)	(0.006)	(0.007)
Married	0.097***	0.091***	0.069***	0.063***
	(0.008)	(0.007)	(0.008)	(0.010)
Age (<30)	0.154***	0.141***	0.125***	0.094***
	(0.015)	(0.014)	(0.014)	(0.017)
Age (30-50)	0.097***	0.085***	0.064***	0.029**
	(0.013)	(0.012)	(0.012)	(0.014)
Age (51-65)	0.098***	0.094***	0.091***	0.069***
	(0.012)	(0.011)	(0.010)	(0.011)
Foreign-born	-0.347***	-0.320***	-0.288***	-0.254***
	(0.010)	(0.011)	(0.010)	(0.015)
Fixed-term contract	0.037***	0.051***	0.065***	0.099***
	(0.010)	(0.009)	(0.008)	(0.013)
Family size (2)	-0.378***	-0.361***	-0.337***	-0.363***
	(0.010)	(0.010)	(0.010)	(0.013)
Family size (3)	-0.606***	-0.589***	-0.574***	-0.601***
	(0.011)	(0.010)	(0.011)	(0.014)
Family size (4)	-0.761***	-0.740***	-0.726***	-0.765***
	(0.012)	(0.011)	(0.012)	(0.015)
Family size (5+)	-0.939***	-0.917***	-0.885***	-0.930***
	(0.015)	(0.015)	(0.015)	(0.019)
North	0.033***	0.038***	0.042***	0.048***
	(0.007)	(0.006)	(0.007)	(0.009)
South	-0.257***	-0.239***	-0.207***	-0.164***
	(0.008)	(0.008)	(0.008)	(0.011)
Constant	7.800***	8.089***	8.330***	8.793***
	(0.045)	(0.043)	(0.043)	(0.055)
Pseudo-R^2	0.2507	0.2337	0.2199	0.2051

Notes: Estimation performed using a conditional quantile regression with 500 bootstrap replications, excluding minors (age <18). Standard errors are reported in parentheses. The dependent variable is $log(C_{over18})$ and the quantiles are 5 (quintile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 53,310.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B3.7: Quintile Results excluding income from self-employed workers.

Variable	**q20**	**q40**	**q60**	**q80**
log(Y)	0.187***	0.183***	0.181***	0.167***
	(0.005)	(0.005)	(0.005)	(0.006)
Unemployment	0.085***	0.091***	0.112***	0.115***
	(0.023)	(0.025)	(0.023)	(0.031)
Retired	-0.090***	-0.079***	-0.076***	-0.101***
	(0.014)	(0.013)	(0.013)	(0.014)
Urban	0.107***	0.115***	0.111***	0.112***
	(0.006)	(0.006)	(0.006)	(0.007)
Male	-0.050***	-0.047***	-0.040***	-0.033***
	(0.006)	(0.006)	(0.006)	(0.008)
Married	0.112***	0.105***	0.081***	0.078***
	(0.008)	(0.008)	(0.008)	(0.010)
Age(<30)	0.118***	0.095***	0.100***	0.046*
	(0.018)	(0.019)	(0.019)	(0.024)
Age(30–50)	0.114***	0.092***	0.088***	0.049***
	(0.015)	(0.014)	(0.015)	(0.018)
Age(51–65)	0.104***	0.101***	0.112***	0.080***
	(0.013)	(0.011)	(0.013)	(0.014)
Foreign	-0.346***	-0.312***	-0.277***	-0.225***
	(0.012)	(0.012)	(0.012)	(0.015)
Fixed-term	0.027***	0.043***	0.055***	0.077***
	(0.010)	(0.011)	(0.011)	(0.013)
Family size (2)	-0.380***	-0.361***	-0.337***	-0.364***
	(0.010)	(0.010)	(0.011)	(0.013)
Family size (3)	-0.607***	-0.584***	-0.574***	-0.597***
	(0.012)	(0.011)	(0.013)	(0.015)
Family size (4)	-0.772***	-0.737***	-0.725***	-0.761***
	(0.013)	(0.012)	(0.014)	(0.017)
Large family (5+)	-0.921***	-0.899***	-0.866***	-0.908***
	(0.017)	(0.018)	(0.018)	(0.019)
North	0.028***	0.034***	0.035***	0.049***
	(0.008)	(0.007)	(0.007)	(0.010)
South	-0.252***	-0.230***	-0.197***	-0.149***
	(0.009)	(0.008)	(0.009)	(0.011)
constant	7.735***	7.984***	8.198***	8.644***
	(0.053)	(0.054)	(0.054)	(0.060)
Pseudo-R^2	0.246	0.228	0.215	0.201

Notes: Estimation performed using a conditional quantile regression with 500 bootstrap replications, excluding self-employed workers. Standard errors are reported in parentheses. The dependent variable is $log(C)$ and the quantiles are 5 (quintile). The interquantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 34,755.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table B3.8: Quintile Regression excluding imputed rents from consumption.

Variable	**q20**	**q40**	**q60**	**q80**
log(Y)	0.206***	0.192***	0.180***	0.160***
	(0.006)	(0.004)	(0.004)	(0.005)
Unemployed	0.117***	0.116***	0.095***	0.087**
	(0.027)	(0.021)	(0.027)	(0.036)
Retired	-0.104***	-0.109***	-0.112***	-0.114***
	(0.016)	(0.014)	(0.016)	(0.015)
Urban	0.091***	0.091***	0.080***	0.082***
	(0.007)	(0.006)	(0.006)	(0.007)
Male	-0.011	-0.012**	-0.011**	-0.007
	(0.007)	(0.006)	(0.006)	(0.007)
Married	0.113***	0.091***	0.069***	0.056***
	(0.010)	(0.009)	(0.009)	(0.010)
Age (<30)	0.231***	0.208***	0.178***	0.143***
	(0.020)	(0.015)	(0.019)	(0.018)
Age (30-50)	0.182***	0.164***	0.138***	0.109***
	(0.018)	(0.014)	(0.017)	(0.017)
Age (51-65)	0.158***	0.147***	0.136***	0.122***
	(0.016)	(0.013)	(0.016)	(0.016)
Foreign-born	-0.225***	-0.203***	-0.187***	-0.180***
	(0.016)	(0.013)	(0.011)	(0.014)
Fixed-term contract	0.059***	0.062***	0.089***	0.112***
	(0.012)	(0.009)	(0.009)	(0.012)
Family size (2)	-0.294***	-0.288***	-0.294***	-0.311***
	(0.014)	(0.012)	(0.013)	(0.015)
Family size (3)	-0.490***	-0.499***	-0.506***	-0.536***
	(0.014)	(0.012)	(0.013)	(0.015)
Family size (4)	-0.621***	-0.632***	-0.649***	-0.699***
	(0.016)	(0.012)	(0.014)	(0.015)
Family size (5+)	-0.806***	-0.799***	-0.803***	-0.843***
	(0.019)	(0.016)	(0.017)	(0.018)
North	0.057***	0.073***	0.061***	0.050***
	(0.008)	(0.007)	(0.007)	(0.009)
South	-0.218***	-0.189***	-0.157***	-0.122***
	(0.009)	(0.009)	(0.008)	(0.010)
Rent	0.065***	0.014*	-0.034***	-0.090***
	(0.010)	(0.008)	(0.008)	(0.010)
Constant	7.001***	7.448***	7.860***	8.423***
	(0.059)	(0.045)	(0.043)	(0.054)
Pseudo-R^2	0.1580	0.1585	0.1546	0.1525

Notes: Estimation performed using a conditional quantile regression with 500 bootstrap replications. Imputed rents excluded from consumptions, only actual rents considered. For this reason, variable *Rent* included. Standard errors are reported in parentheses. The dependent variable is $log(C_{NOrent})$ and the quantiles are 5 (quintile). The inter-quantile differences of $log(Y)$ are mostly significant and residuals are Normally-distributed (Appendix B4). Sample: N = 53,309.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Appendix B4

Diagnostic tests

Table B4.1: White test, Cameron & Trivedi's IM-Test

χ^2	**2018**	**2019**	**2020**	**2021**	**2022**	**P** $> \chi^2$
Heteroskedasticity	2467.57	4863.3	12069.98	2027.4	2179.07	0.00
Skewness	395.78	1341.3	4344.25	566.50	470.63	0.00
Kurtosis	14.78	23.23	37.81	83.12	80.24	0.00
Total	2878.14	6227.83	16452.04	2581.16	2825.81	0.00

Notes: χ^2-test on heteroskedasticity, skewness and kurtosis for the OLS regressions (Appendix B1). Null hypothesis H_0 (Homoskedasticity) strongly rejected in favour of the alternative H_a (Unrestricted heteroskedasticity).

Table B4.2: Machado-Santos Silva test for heteroskedasticity.

MSS	General	Services	Nondurables	Durables	Wealth	Property
χ^2	274.192	91.890	14.006	347.041	71.994	41.996
P $> \chi^2$	0.000	0.000	0.001	0.000	0.000	0.000
MSS	Quadratic	North	Centre	South	Urban	Rural
χ^2	170.815	70.509	50.034	69.904	199.315	74.733
P $> \chi^2$	0.000	0.000	0.000	0.000	0.000	0.000
MSS	No-self	Under 65	Over 18	No fig.rent	Equivalised	UQR
χ^2	117.234	218.191	138.542	52.828	1097.477	731.360
P $> \chi^2$	0.000	0.000	0.000	0.000	0.000	0.000
MSS	Q2018	Q2019	Q2020	Q2021	Q2022	
χ^2	262.977	471.482	232.067	270.508	333.669	
P $> \chi^2$	0.000	0.000	0.000	0.000	0.000	

Notes: This test is performed to assess the heteroskedasticity of different models. Variables considered are the fitted values of $log(C)$ and its squares. The null hypothesis H_0 is a constant variance. Since rejected in many cases, bootstrapped robust-standard errors are used (Quantile Regression is robust by construction).

Table B4.3: Quantile regression Wald test to assess interdecile difference.

Quantile	General		Services		Nondurables		Durables		Wealth		Property	
logY	stat	p-value	stat.	p-value	stat.	p-value	stat.	p-value	stat.	p-value	stat.	p-value
(q10)=(q20)	4.89	0.027	3.04	0.081	5.42	0.020	22.32	0.000	0.06	0.809	1.54	0.215
(q20)=(q30)	0.00	0.949	0.01	0.917	3.38	0.066	19.40	0.004	4.54	0.033	3.15	0.076
(q30)=(q40)	9.15	0.003	4.88	0.027	0.03	0.852	24.77	0.000	6.41	0.011	0.01	0.924
(q40)=(q50)	0.11	0.742	8.88	0.003	10.15	0.001	2.16	0.142	5.07	0.024	2.37	0.124
(q50)=(q60)	12.78	0.000	0.79	0.376	2.26	0.133	5.21	0.022	1.56	0.211	1.27	0.259
(q60)=(q70)	20.37	0.000	2.07	0.151	0.38	0.538	11.44	0.001	3.18	0.074	6.25	0.012
(q70)=(q80)	14.93	0.000	10.09	0.001	2.22	0.136	23.19	0.000	0.32	0.569	8.07	0.004
(q80)=(q90)	6.81	0.000	30.56	0.000	2.52	0.112	3.64	0.056	3.43	0.064	0.20	0.651
Quantile	North		Centre		South		Urban		Rural		Quadratic	
(q10)=(q20)	2.72	0.099	0.77	0.380	0.34	0.557	6.54	0.011	0.56	0.453	1.22	0.270
(q20)=(q30)	0.64	0.425	0.79	0.375	0.03	0.857	4.66	0.031	0.01	0.939	0.09	0.761
(q30)=(q40)	0.02	0.875	2.18	0.140	0.08	0.771	1.12	0.291	5.36	0.021	13.29	0.000
(q40)=(q50)	5.31	0.021	1.35	0.245	0.04	0.849	13.93	0.000	8.66	0.003	7.85	0.005
(q50)=(q60)	8.37	0.004	0.13	0.718	0.01	0.905	11.38	0.001	2.20	0.138	3.87	0.049
(q60)=(q70)	8.69	0.003	5.27	0.022	6.21	0.013	33.37	0.000	12.45	0.000	10.06	0.001
(q70)=(q80)	21.76	0.000	1.86	0.172	2.33	0.127	28.61	0.000	10.01	0.002	1.39	0.239
(q80)=(q90)	5.19	0.023	8.43	0.004	0.00	0.977	29.05	0.000	6.77	0.009	1.19	0.276

Notes: This test is performed to assess the interquantile difference of the estimation of $log(Y)$. The null hypothesis of interest is that the slope coefficients of the quantiles are identical, strongly rejected by a p-value = 0. The test statistic is described in Koenker and Bassett (1982).

Table B4.4: Quantile regression Wald test to assess interquintile difference.

Quantiles	No-self		Under 65		Over 18		No fig.rent		Equivalised		UQR	
logY	stat	p-value	stat.	p-value	stat.	p-value	stat.	p-value	stat.	p-value	stat.	p-value
(q20)=(q40)	0.89	0.345	12.85	0.000	3.83	0.050	8.84	0.003	21.81	0.000	0.104	0.253
(q40)=(q60)	0.15	0.703	2.66	0.103	1.30	0.255	11.99	0.001	50.07	0.000	0.542	0.538
(q60)=(q80)	8.19	0.004	81.35	0.000	25.94	0.000	25.94	0.000	112.58	0.000	0.000	1.000
Quantiles	Q2018		Q2019		Q2020		Q2021		Q2022			
	stat	p-value	stat.	p-value	stat.	p-value	stat.	p-value	stat.	p-value		
(q20)=(q40)	74.33	0.000	22.76	0.000	12.27	0.001	8.36	0.004	3.67	0.056		
(q40)=(q60)	20.51	0.000	91.14	0.000	0.32	0.569	17.58	0.000	4.40	0.036		
(q60)=(q80)	15.11	0.000	47.01	0.000	13.67	0.000	10.99	0.001	40.92	0.000		

Notes: This test is performed to assess the interquantile difference of the estimation of $log(Y)$. The null hypothesis of interest is that the slope coefficients of the quantiles are identical, strongly rejected by a p-value = 0. The test statistic is described in Koenker and Bassett (1982).

Table B4.5: Kurtosis statistics for each regression.

General	Services	Nondurables	Durables	Wealth	Property
3.347	3.751	4.634	4.071	3.789	3.331
Quadratic	North	Centre	South	Urban	Rural
3.306	3.401	3.278	3.225	3.442	3.308
No-self	Under 65	Over 18	No fig.rent	Equivalised	UQR
3.366	3.324	3.340	3.874	3.600	3.248
Q2018	Q2019	Q2020	Q2021	Q2022	
3.608	3.696	3.448	3.268	3.541	

Notes: For each regression, kurtosis of residuals is reported. Normality of a distribution requires a statistic value of 3.

Table B4.6: Shapiro–Wilk Test for Normality of Residuals

Table	Obs	W	V	z	Prob > z
General	53,310	0.996	83.529	12.286	0.000
Services	53,310	0.988	242.260	15.243	0.000
Nondurables	53,118	0.986	267.161	15.514	0.000
Durables	53,060	0.989	206.861	14.803	0.000
North	53,310	0.997	61.238	11.425	0.000
Centre	53,310	0.998	35.127	9.881	0.000
South	53,310	0.999	27.846	9.236	0.000
Urban	53,310	0.996	71.760	11.865	0.000
Rural	53,310	0.998	42.612	10.418	0.000
Q2022	53,310	0.996	77.221	12.068	0.000
Q2021	53,623	0.998	39.641	10.218	0.000
Q2020	47,649	0.998	41.689	10.337	0.000
Q2019	37,713	0.995	68.323	11.657	0.000
Q2018	36,744	0.996	51.795	10.887	0.000
Wealth	15,420	0.997	23.047	8.493	0.000
Property	23,007	0.997	28.752	9.176	0.000
Quadratic	53,310	0.997	66.644	11.659	0.000
No-self	34,755	0.995	66.169	11.55	0.000
Under 65	53,310	0.996	70.673	11.822	0.000
Over 18	53,310	0.996	71.526	11.856	0.000
No fig.rent	53,309	0.997	64.913	11.586	0.000
Equivalised	60,225	0.994	118.557	13.285	0.000
UQR	53,310	0.999	23.388	8.752	0.000

Notes: The Shapiro-Wilk test assesses the Normality of residuals for large-sample regressions. The test statistic W measures how closely the residuals have a Normal distribution (W=1), so all of them are approximately Gaussian.

Appendix B5

Details on the dataset AD-HBS

1. The sample contains: 42,144 individuals (18,342 households) in 2018; 42,744 (18,718) in 2019; 58,598 (25,668) in 2020; 64,544 (28,608) in 2021; and 62,920 observations (28,416) in 2022.

2. The information on consumption categories is limited to the first nine classes (out of thirteen) which are available for all the years. The purchase of durable goods is partially available, covering some expenses with yearly amortisation (like vehicles). Others are missing (e.g. dwellings), but the fixed asset value is controlled by the disaggregation of the ISEE values.

3. The ISEE results from the sum of the household income indicator (ISR) and the household wealth indicator (ISP). Although the declaration is mandatory for most of the means-tested transfers, the rate of declaration is still below the 50% and subject to strong auto-selection of compilers. There are many reasons for that, from the difficulty in dealing with bureaucracy to the fear of tax assessments, or the cost of doing it without any expected benefit.

4. In Italy, there are 14 Metropolitan Cities as individuated by *l.56/14* (GU n.81, 2014): Rome, Milan, Naples, Turin, Florence, Venice, Genoa, Bologna, Bari, Reggio Calabria, Palermo, Catania, Messina, Cagliari.

5. To compare descriptive statistics over time, in Table 2.1 some population weights are used to balance observations between years. Nonetheless, the distribution of the Italian population is preserved throughout the sample, and the yearly-specific descriptive statistics are provided in the following tables.

Descriptive statistics per year

Table B5.1: Descriptive statistics in 2022.

Variable	Mean	Median	St.Dev..	Min	Max
Age	47.45	51	23.1137	0	102
Family size	2.21	3	1.2883	1	11
Female	0.5199	1	0.4975	0	1
Married	0.4505	0	0.4975	0	1
North	0.4327	0	0.4955	0	1
Centre	0.2323	0	0.4223	0	1
South & Island	0.3350	0	0.4720	0	1
Metropolitan area	0.1562	0	0.3631	0	1
Medium-size cities	0.3009	0	0.4587	0	1
Small municipalities	0.5428	1	0.4982	0	1
Age(<30)	0.2496	0	0.4328	0	1
Age(30-50)	0.2503	0	0.4332	0	1
Age(51-65)	0.2501	0	0.4331	0	1
Age(>65)	0.2500	0	0.4330	0	1
Family size (1)	0.1526	0	0.3596	0	1
Family size (2)	0.2923	0	0.4548	0	1
Family size (3)	0.2313	0	0.4217	0	1
Family size (4)	0.2395	0	0.4268	0	1
Family size (5+)	0.0844	0	0.2779	0	1
Tenants (rent)	0.1597	0	0.3663	0	1
Home-ownership	0.7611	1	0.4264	0	1
Unemployment rate	0.0595	0	0.2365	0	1

Notes: Descriptive statistics of the AD-HBS dataset in 2022. Values are to be intended as share of the total, except for *Age* and *Family size*.

Table B5.2: Descriptive statistics in 2021.

Variable	**Mean**	**Median**	**St.Dev.**.	**Min**	**Max**
Age	46.79	50	23.0106	0	105
Family size	2.26	3	1.2857	1	10
Female	0.5179	1	0.4997	0	1
Married	0.4515	0	0.4977	0	1
North	0.4407	0	0.4965	0	1
Centre	0.2331	0	0.4228	0	1
South & Island	0.3262	0	0.4688	0	1
Metropolitan area	0.1643	0	0.3705	0	1
Medium-size cities	0.3009	0	0.4587	0	1
Small municipalities	0.5348	1	0.4988	0	1
Age(<30)	0.2567	0	0.4368	0	1
Age(30-50)	0.2583	0	0.4377	0	1
Age(50-65)	0.2476	0	0.4316	0	1
Age(>65)	0.2373	0	0.4254	0	1
Family size (1)	0.1438	0	0.3509	0	1
Family size (2)	0.2838	0	0.4508	0	1
Family size (3)	0.2412	0	0.4278	0	1
Family size (4)	0.2362	0	0.4248	0	1
Family size (5+)	0.0950	0	0.2932	0	1
Tenants (rent)	0.1589	0	0.3656	0	1
Home-ownership	0.7658	1	0.4235	0	1
Unemployment rate	0.0660	0	0.2483	0	1

Notes: Descriptive statistics of the AD-HBS dataset in 2021. Values are to be intended as fraction (percentage) of the total, except for *Age* and *Family size*.

Table B5.3: Descriptive statistics in 2020.

Variable	**Mean**	**Median**	**SD**	**Min**	**Max**
Age	46.44	49	23.2258	0	104
Family size	2.28	3	1.2841	1	12
Female	0.5200	1	0.4996	0	1
Married	0.4553	0	0.4980	0	1
North	0.4502	0	0.4975	0	1
Centre	0.2261	0	0.4183	0	1
South & Island	0.3237	0	0.4679	0	1
Metropolitan area	0.1693	0	0.3750	0	1
Medium-size cities	0.3013	0	0.4588	0	1
Small municipalities	0.5295	1	0.4991	0	1
Age(<30)	0.2611	0	0.4392	0	1
Age(30-50)	0.2638	0	0.4407	0	1
Age(50-65)	0.2372	0	0.4254	0	1
Age(>65)	0.2379	0	0.4258	0	1
Family size (1)	0.1373	0	0.3442	0	1
Family size (2)	0.2826	0	0.4503	0	1
Family size (3)	0.2398	0	0.4270	0	1
Family size (4)	0.2479	0	0.4318	0	1
Family size (5+)	0.0925	0	0.2897	0	1
Tenants (rent)	0.1632	0	0.3696	0	1
Home-ownership	0.7609	1	0.4265	0	1
Unemployment rate	0.0705	0	0.2559	0	1

Notes: Descriptive statistics of the AD-HBS dataset in 2020. Values are to be intended as fraction (percentage) of the total, except for *Age* and *Family size*.

Table B5.4: Descriptive statistics in 2019.

Variable	**Mean**	**Median**	**St.Dev.**.	**Min**	**Max**
Age	46.50	49	23.3478	0.	109
Family size	2.29	3	1.3110	1	9
Female	0.5203	1	0.4996	0	1
Married	0.4548	0	0.4980	0	1
North	0.4567	0	0.4981	0	1
Centre	0.1956	0	0.3967	0	1
South & Island	0.3477	0	0.4762	0	1
Metropolitan area	0.1461	0	0.3532	0	1
Medium-size cities	0.2814	0	0.4497	0	1
Small municipalities	0.5724	1	0.4947	0	1
Age(<30)	0.2628	0	0.4402	0	1
Age(30-50)	0.2625	0	0.4400	0	1
Age(50-65)	0.2335	0	0.4231	0	1
Age(>65)	0.2412	0	0.4278	0	1
Family size (1)	0.1389	0	0.3458	0	1
Family size (2)	0.2784	0	0.4482	0	1
Family size (3)	0.2355	0	0.4243	0	1
Family size (4)	0.2430	0	0.4289	0	1
Family size (5+)	0.1043	0	0.3056	0	1
Tenants (rent)	0.1696	0	0.3753	0	1
Home-ownership	0.7518	1	0.4319	0	1
Unemployment rate	0.0722	0	0.2589	0	1

Notes: Descriptive statistics of the AD-HBS dataset in 2019. Values are to be intended as fraction (percentage) of the total, except for *Age* and *Family size*.

Table B5.5: Descriptive statistics in 2018.

Variable	**Mean**	**Median**	**St.Dev..**	**Min**	**Max**
Age	46.14	48	23.2652	0	105
Family size	2.30	3	1.2998	1	11
Female	0.5158	1	0.4998	0	1
Married	0.4617	0	0.4985	0	1
North	0.4522	0	0.4977	0	1
Centre	0.1970	0	0.3977	0	1
South & Island	0.3508	0	0.4772	0	1
Metropolitan area	0.1460	0	0.3531	0	1
Medium-size cities	0.2781	0	0.4481	0	1
Small municipalities	0.5759	1	0.4942	0	1
Age(<30)	0.2637	0	0.4407	0	1
Age(30-50)	0.2681	0	0.4430	0	1
Age(50-65)	0.2329	0	0.4227	0	1
Age(>65)	0.2353	0	0.4242	0	1
Family size (1)	0.1360	0	0.3428	0	1
Family size (2)	0.2795	0	0.4488	0	1
Family size (3)	0.2340	0	0.4233	0	1
Family size (4)	0.2481	0	0.4319	0	1
Family size (5+)	0.1024	0	0.3032	0	1
Tenants (rent)	0.1728	0	0.3780	0	1
Home-ownership	0.7428	1	0.4371	0	1
Unemployment rate	0.0752	0	0.2637	0	1

Notes: Descriptive statistics of the AD-HBS dataset in 2018. Values are to be intended as fraction (percentage) of the total, except for *Age* and *Family size*.

Appendix B6

Model-based experiment details

A Simple Aiyagari Model

We consider a standard incomplete-markets economy with infinitely lived, ex-ante identical households who face uninsurable idiosyncratic income risk. Preferences are time separable with constant relative risk aversion (CRRA). The individual problem is:

$$\max_{\{c_t, a_{t+1}\}_{t\geq 0}} \quad \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\gamma} - 1}{1-\gamma} \tag{B1}$$

$$\text{s.t.} \quad c_t + a_{t+1} \leq y_t + (1+r)a_t, \tag{B2}$$

$$a_{t+1} \geq 0. \tag{B3}$$

Idiosyncratic labor income has a high-persistent (z) and a low-transitory component (v):

$$y_t = \exp\big(z_t + v_t\big), \tag{B4}$$

$$z_t = \rho_\eta \, z_{t-1} + \eta_t, \tag{B6.1}$$

$$v_t = \rho_\epsilon \, v_{t-1} + \epsilon_t, \tag{B5}$$

where $\epsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ and $\eta_t \sim \mathcal{N}(0, \sigma_\eta^2)$ are i.i.d., mutually independent innovations.

Let $c(a, z, v)$ and $a'(a, z, v)$ denote the optimal policy functions for consumption and next period assets, with current state (a, z, v).

To map the model to the empirical elasticity of expenditure with respect to income (EIE), we follow the convention of normalizing mean income to one and consider the relevant shock parameters (ρ_η, ρ_ϵ, σ_η, σ_ϵ) to be able to map from the structural decision rules to the impact

response of consumption that we use to discipline the EIEs in the data.

The Present–Value (PV) Multiplier

This appendix formalises the *present–value multiplier* that links the persistence of income shocks to the consumption response used in Section 2.8. Let (net-of-trend) income follow an AR(1) process,

$$y_{t+1} = \rho\, y_t + \varepsilon_{t+1}, \qquad |\rho| < 1, \tag{B6.2}$$

and let $R > 0$ denote the gross real interest factor (e.g., at annual frequency $R = 1 + r$). An innovation ε_t at time t generates the expected income path $\{\varepsilon_t,\ \rho\,\varepsilon_t,\ \rho^2\varepsilon_t, \ldots\}$. The present value (PV) of that path, discounted at R, is

$$\mathrm{PV}(\varepsilon_t) = \varepsilon_t \sum_{j=0}^{\infty} \left(\frac{\rho}{R}\right)^j = \frac{\varepsilon_t}{1 - \rho/R} \equiv M(\rho, R)\, \varepsilon_t, \qquad \text{for } |\rho| < R. \tag{B6.3}$$

We call $M(\rho, R) = \big(1 - \rho/R\big)^{-1}$ the *PV multiplier*: it scales a one-off income innovation into the associated change in permanent wealth.

If the marginal propensity to consume out of wealth is κ (the "annuity" factor; at annual frequency $\kappa \approx r$ for small r), the optimal response of consumption to the innovation is approximately

$$\Delta c_t \approx \kappa \cdot \mathrm{PV}(\varepsilon_t) = \kappa\, M(\rho, R)\, \varepsilon_t. \tag{B6.4}$$

Hence, lower persistence (ρ) reduces $M(\rho, R)$ and, holding preferences and liquidity conditions fixed, implies a smaller consumption response to the same income innovation. In our empirical framework, this maps into a lower EIE when the income process becomes less persistent.

As discussed in Section 2.8, when the estimated shock process features lower persistence and variance (for given preference parameters), agents accumulate larger precautionary buffers and the consumption policy becomes locally flatter, which—via the PV multiplier—translates into lower EIEs across the distribution. The PV mechanism provides the central identification channel through which differences in the composition and persistence of shocks across periods map into the heterogeneous consumption elasticities we document.

Appendix C1

Difference-in-differences

Diff-in-diff primary assumptions and parallel trends

1. PS overlap (*common support*): $0 < P(D = 1|X) < 1$

   Assumption 1 assumes that everyone has a non-zero probability either of receiving each treatment level or not.

2. *Unconfoundedness*: $Y(0), Y(1) \perp\!\!\!\perp D|X$

   Assumption 2 assumes that there are no unmeasured confounders: the treatment status is not related to the trend over time that would be observed under the control condition, conditional on the observed covariates X.

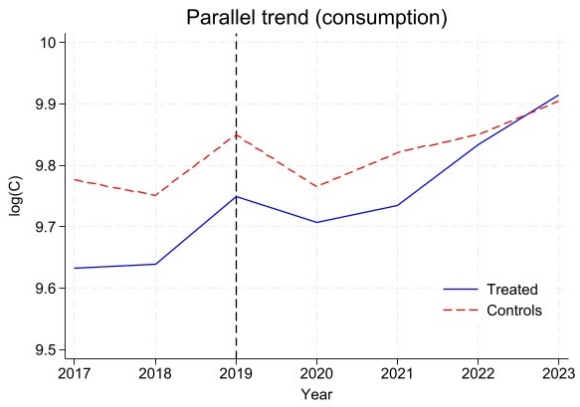
3. *Exogeneity*: $X_1 = X_0 = X$.

   Assumption 3 claims that the covariates X are not affected by the treatment.

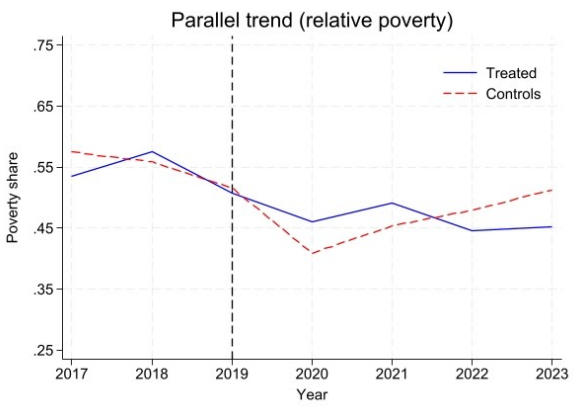
4. *Stable Unit Treatment Value* (SUTVA)

   A final assumption is the standard causal inference assumption of the stable unit treatment value assumption (see Rubin (1977) and Imbens and Rubin (2015)), which assumes that all potential outcomes are not affected by treatment assignments of any other subjects and that there are no spillover effects.

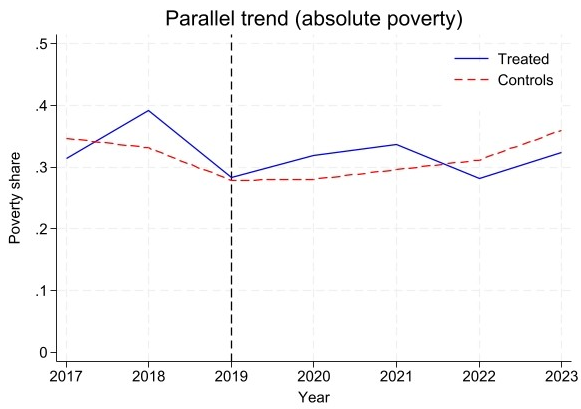
Parallel trends



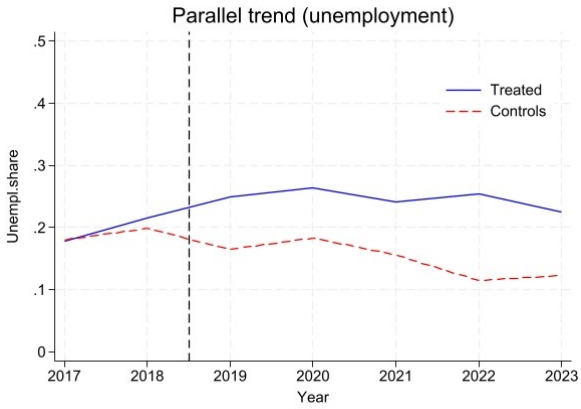
(a) Consumption



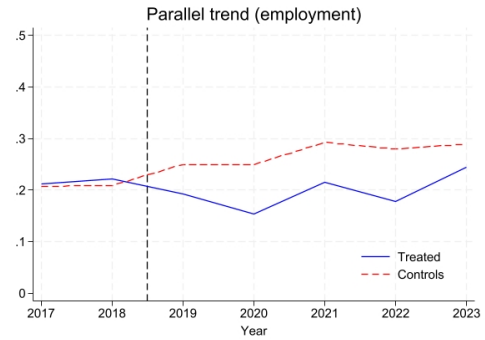
(b) Relative poverty



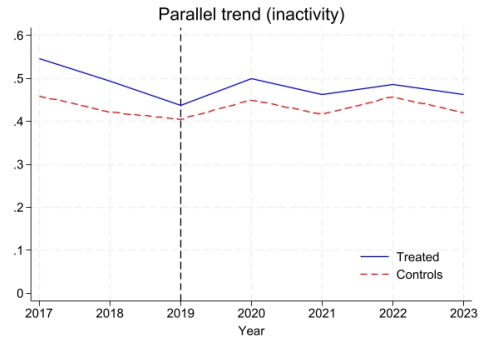
(c) Absolute Poverty



(d) Unemployment



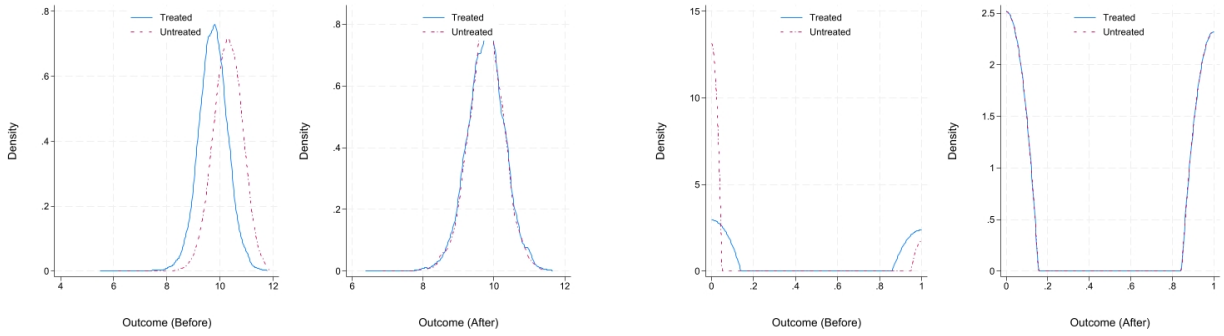
(e) Employment



(f) Inactivity

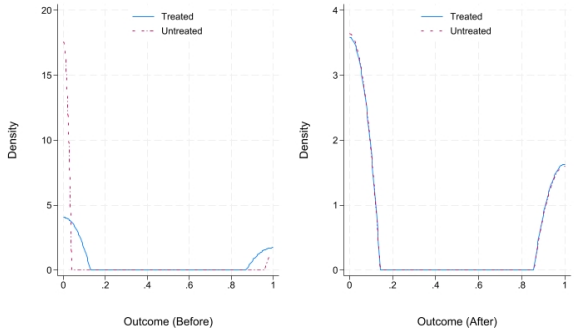
Figure C1.1: Parallel trends for all the outcome variables.

Matching process

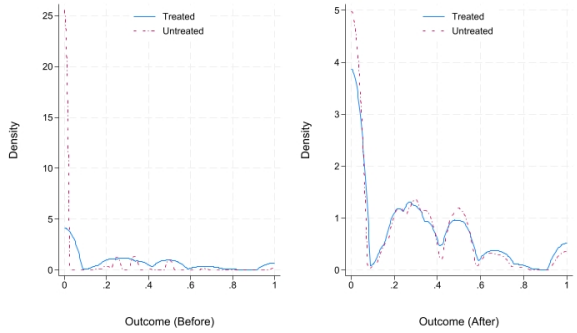


(a) Consumption

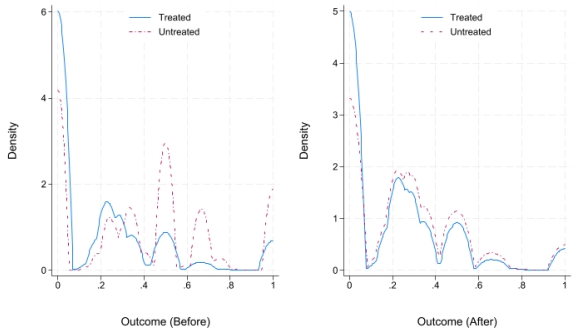
(b) Relative poverty



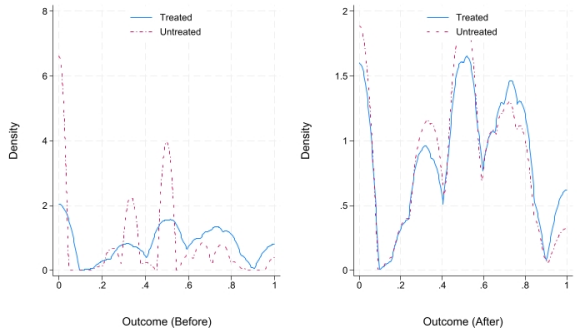
(c) Absolute Poverty



(d) Unemployment



(e) Employment



(f) Inactivity

Figure C1.2: The outcome density before/after matching Treated - Controls.

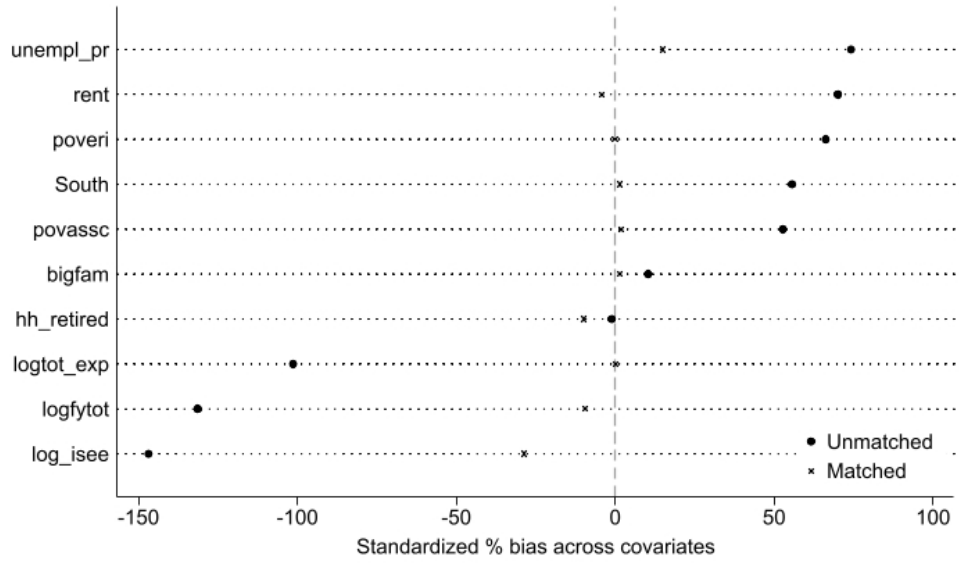
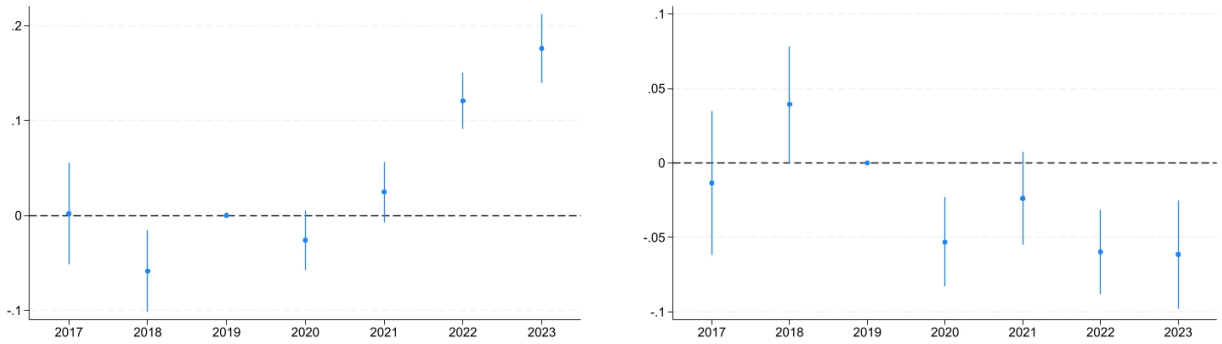


Figure C1.3: The reduction in selection bias of variables after matching.

Event studies



(a) Consumption **(b)** Poverty

Figure C1.4: Event studies of consumption and poverty, year by year.

Robustness checks

Table C1.1: Regression with fake treatment delivered in 2018.

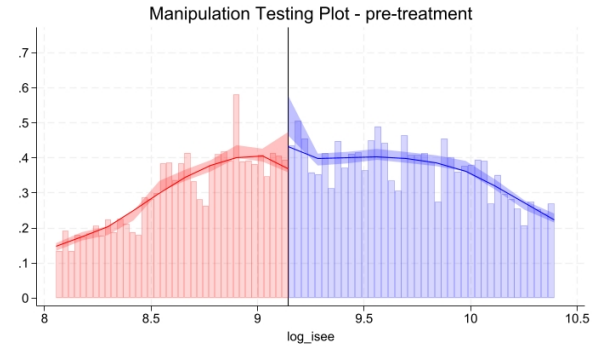
Variable	Aggr.Cons.	Rel.Poverty	Abs.Poverty	Unemployment	Employment	Inactivity
Eligible	-0.061**	0.026	0.010	0.014	-0.007	0.032**
	(0.028)	(0.028)	(0.026)	(0.015)	(0.013)	(0.014)
Post-2018	0.108***	-0.082***	-0.045***	-0.022**	0.018**	0.013
	(0.015)	(0.015)	(0.014)	(0.009)	(0.007)	(0.008)
Fake-treatment	0.012	-0.026	0.019	0.007	-0.017	-0.005
	(0.029)	(0.029)	(0.027)	(0.015)	(0.013)	(0.015)
Retired	0.031***	0.014	-0.046***	-0.140***	-0.129***	-0.181***
	(0.011)	(0.011)	(0.011)	(0.006)	(0.005)	(0.006)
Children	0.131***	-0.026**	-0.057***	-0.187***	-0.068***	0.211***
	(0.011)	(0.011)	(0.010)	(0.006)	(0.005)	(0.005)
Age (avg)	-0.298***	-0.080**	-0.090***	-0.170***	-0.313***	0.101***
	(0.035)	(0.035)	(0.033)	(0.020)	(0.016)	(0.018)
Married	0.026***	-0.002	-0.014**	-0.023***	0.027***	0.008**
	(0.007)	(0.007)	(0.007)	(0.004)	(0.003)	(0.004)
Single	-0.315***	-0.257***	-0.116***	-0.022***	0.048***	-0.125***
	(0.012)	(0.012)	(0.011)	(0.006)	(0.005)	(0.006)
Large family	0.160***	0.147***	0.138***	0.010*	-0.051***	0.048***
	(0.009)	(0.009)	(0.008)	(0.005)	(0.004)	(0.004)
Tenants (rent)	-0.188***	0.133***	0.100***	-0.018***	0.051***	-0.033***
	(0.007)	(0.007)	(0.007)	(0.004)	(0.003)	(0.004)
Urban	0.024***	-0.015**	0.004	0.004	-0.001	0.007**
	(0.006)	(0.006)	(0.006)	(0.004)	(0.003)	(0.003)
North	-0.035***	0.030***	0.072***	-0.001	-0.009*	-0.010*
	(0.011)	(0.011)	(0.010)	(0.006)	(0.005)	(0.006)
South	-0.104***	0.114***	-0.021**	0.043***	-0.047***	0.028***
	(0.009)	(0.009)	(0.009)	(0.005)	(0.004)	(0.005)
Education	0.603***	-0.459***	-0.293***	0.129***	0.268***	-0.375***
	(0.021)	(0.021)	(0.020)	(0.012)	(0.010)	(0.011)
constant	9.641***	0.675***	0.472***	0.361***	0.245***	0.485***
	(0.028)	(0.028)	(0.027)	(0.016)	(0.013)	(0.014)
N	21,944	21,944	21,944	23,075	21,930	21,944
AIC	28,914	29,078	26,662	5,466	4,126	510
R^2	0.188	0.119	0.066	0.109	0.173	0.357

Notes: Estimation performed using a difference-in-differences regression combined with propensity score matching, delivering a fake-treatment in 2018. Standard errors are reported in parentheses.

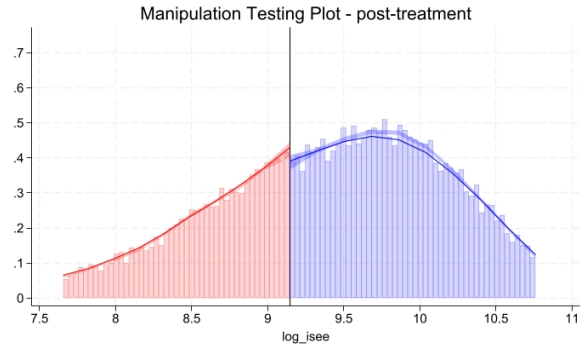
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Appendix C2

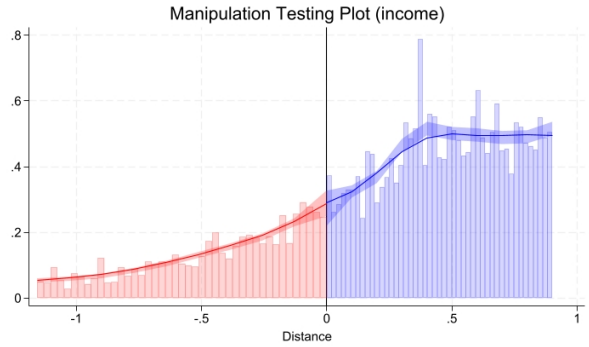
Difference-in-discontinuity



(a) ISEE (pre)



(b) ISEE (post)

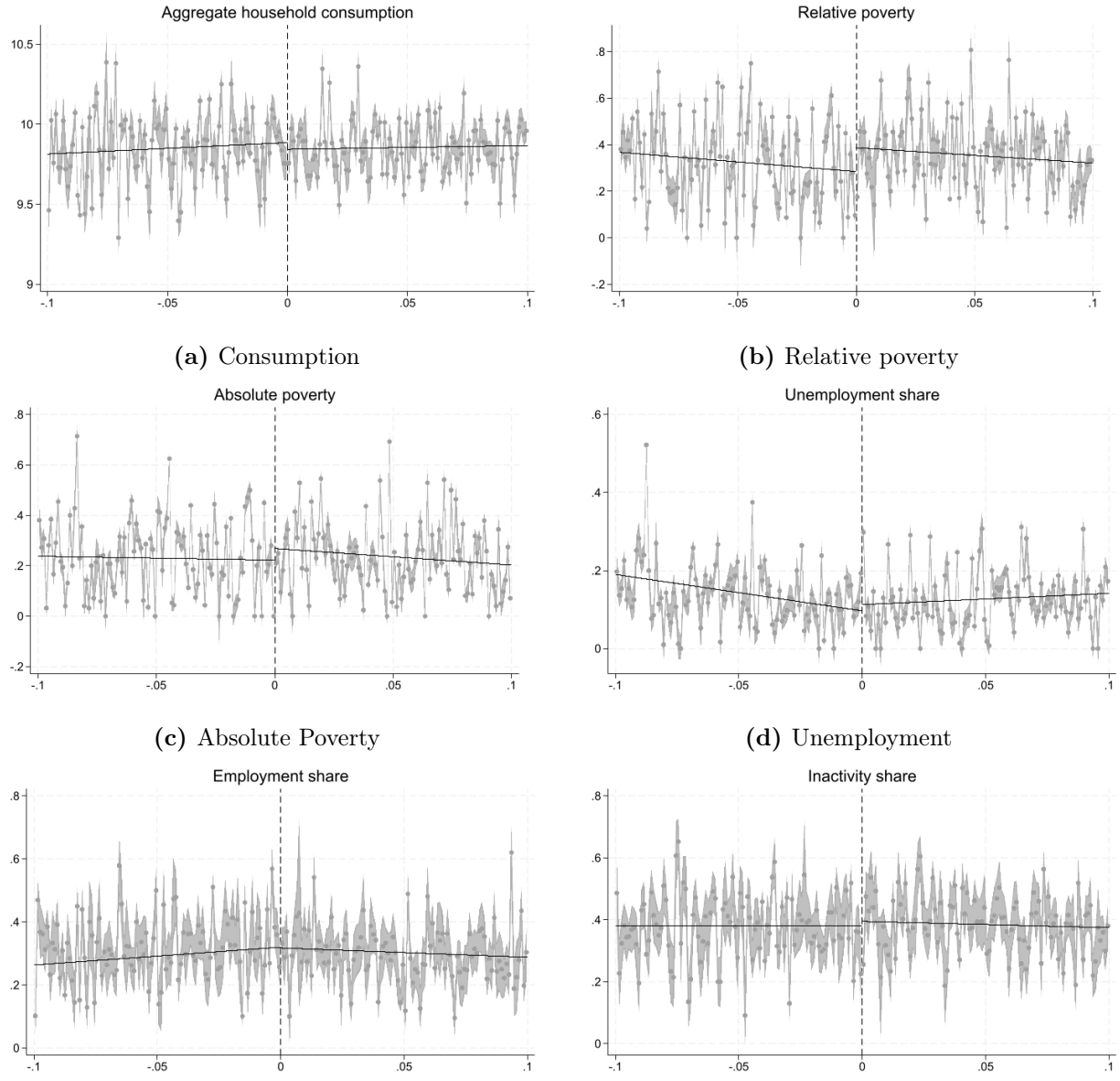


(c) Income (pre)

(d) Income (post)

Figure C2.1: McCrary manipulation testing plots.

Discontinuity plots



(a) Consumption

(b) Relative poverty

(c) Absolute Poverty

(d) Unemployment

(e) Employment

(f) Inactivity

Figure C2.2: Discontinuity plots for each dependent variable.

Table C2.1: Diff-in-disc regressions with fixed ISEE threshold.

Variable	Aggr.Cons.	Rel.Poverty	Abs.Poverty	Unemployment	Employment	Inactivity
Distance	0.092***	-0.040***	-0.032***	-0.038***	0.030***	0.004***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Post-Treatment	-0.011**	0.016***	0.017***	-0.006***	0.029***	-0.021***
	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Eligible / Below	-0.212***	0.147***	0.089***	0.032***	-0.038***	-0.001
	(0.007)	(0.007)	(0.006)	(0.003)	(0.003)	(0.003)
Treated	0.060***	-0.047***	-0.013**	0.004	-0.027***	0.032***
	(0.007)	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)
Retired	0.019***	-0.001	-0.032***	-0.059***	-0.231***	-0.140***
	(0.005)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)
Children	0.122***	-0.040***	-0.037***	-0.086***	-0.063***	0.113***
	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Age (avg)	-0.429***	-0.033**	0.020*	-0.040***	-0.317***	-0.096***
	(0.016)	(0.013)	(0.011)	(0.007)	(0.009)	(0.010)
Married	0.017***	-0.001	-0.001	-0.014***	0.020***	-0.006***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Single	-0.374***	-0.160***	-0.055***	-0.013***	0.071***	-0.136***
	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Large family	0.163***	0.098***	0.082***	0.004***	-0.072***	0.074***
	(0.004)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Tenants (rent)	-0.206***	0.129***	0.093***	0.007***	0.023***	-0.032***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Urban	0.028***	-0.009***	0.007***	0.001	-0.001	0.000
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Education	0.624***	-0.347***	-0.198***	0.054***	0.364***	-0.309***
	(0.009)	(0.008)	(0.007)	(0.004)	(0.005)	(0.005)
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
N	117,553	117,553	117,553	117,553	117,553	117,553
AIC	138,210	101,423	63,792	69,763	35,290	36,172
R^2	0.395	0.194	0.121	0.152	0.367	0.335

Notes: Estimation performed using a difference-in-discontinuity regression around the fixed ISEE threshold: €9,360. The dependent variables are reported in the first row. Standard errors are reported in parentheses.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Bibliography

AA.VV. (2021). *Relazione del comitato scientifico per la valutazione del reddito di cittadinanza* (Report). Ministero del lavoro e delle politiche sociali.

AA.VV. (2024). *Report on equitable and sustainable wellbeing (bes) indicators* (Annual report). Economic Financial Analysis and Research Directorate - Department of the Treasury. Ministry of Economy; Finance (MEF).

Accetturo, A., Albanese, G., Ballatore, R. M., Ropele, T., & Sestito, P. (2022). *Regional inequality in italy in the face of economic crises, recovery, and the health emergency* (Occasional Papers No. 685). Bank of Italy. Bank of Italy.

Aguiar, M., & Bils, M. (2015). *Has consumption inequality mirrored income inequality? American Economic Review*, *105*(9), 2725–56.

Aiyagari, S. R. (1994). *Uninsured idiosyncratic risk and aggregate saving. The Quarterly Journal of Economics*, *109*(3), 659–684.

Albacete, N., Fessler, P., & Pekanov, A. (2024). *The role of mpc heterogeneity for fiscal and monetary policy in the euro area* (Working Paper No. 254). Oesterreichische Nationalbank (Austrian Central Bank). Oesterreichische Nationalbank.

Albacete, N., Fessler, P., & Pekanov, A. (2025). *The role of mpc heterogeneity for fiscal policy in the euro area. Journal of Macroeconomics*, 103719.

Albanese, G., Barone, G., & De Blasio, G. (2023). *The impact of place-based policies on interpersonal income inequality. Economica*, *90*(358), 508–530.

Alberini, A., Gans, W., & Velez-Lopez, D. (2011). *Residential consumption of gas and electricity in the us: The role of prices and income. Energy Economics*, *33*(5), 870–881.

Andreolli, M., & Surico, P. (2026). *'less is more': Consumer spending and the size of economic stimulus payments. American Economic Journal: Macroeconomics*, *18*(1), 34–68.

Andreyeva, T. M., Long, M. W., & Brownell, K. D. (2010). *The impact of food prices on consumption: A systematic review of research on the price elasticity of demand for food. American Journal of Public Health*, *100*(2), 216–222.

Aprea, M., Battles, S., Gallo, G., Passeri, S., Palombi, M., Raitano, M., Romano, E., & Zoppoli, P. (2023). *Measuring poverty in italy: How the ad-hbs dataset can offer new insights* (Working Paper No. 5). Department of the Treasury. Ministry of Economy; Finance (MEF).

Aprea, M., Gallo, G., & Raitano, M. (2024). *The large family penalty in italy: Poverty and eligibility to minimum incomes. International Journal of Social Welfare*, *34*(2), 1–17.

Arellano, M., Blundell, R., Bonhomme, S., & Light, J. (2024). *Heterogeneity of consumption responses to income shocks in the presence of nonlinear persistence. Journal of Econometrics*, *240*(2), None.

Atkin, D., Faber, B., Fally, T., & Gonzalez-Navarro, M. (2024). *Measuring welfare and inequality with incomplete price information. The Quarterly Journal of Economics*, *139*(1), 419–475.

Atkinson, A. B. (1995). *Public economics in action: The basic income/flat tax proposal*. Oxford University Press.

Attanasio, O. P., & Pistaferri, L. (2014). *Consumption inequality over the last half century: Some evidence using the new psid consumption measure. American Economic Review*, *104*(5), 122–126.

Attanasio, O. P., & Weber, G. (1995). *Is consumption growth consistent with intertemporal optimization? evidence from the consumer expenditure survey. Journal of Political Economy*, *103*(6), 1121–1157.

Auclert, A. (2019). *Monetary policy and the redistribution channel. American Economic Review*, *109*(6), 2333–2367.

Auclert, A., Bardóczy, B., & Rognlie, M. (2023). *Mpcs, mpes, and multipliers: A trilemma for new keynesian models. The Review of Economics and Statistics*, *105*(3), 700–712.

Baker, A., Callaway, B., Cunningham, S., Goodman-Bacon, A., & Sant'Anna, P. H. (forthcoming). *Difference-in-differences designs: A practitioner's guide.*

Baldini, M., Gallo, G., & Gatta, A. (2023). *The take up of the citizenship income* (Annual report No. 22). INPS. Istituto Nazionale della Previdenza Sociale.

Baldini, M., Gallo, G., Lusignoli, L., Toso, S., et al. (2019). *Le politiche per l'assistenza: Il reddito di cittadinanza. CAPPAPERS.*

Banks, J., Blundell, R. W., & Lewbel, A. (1997). *Quadratic engel curves and consumer demand. The Review of Economics and Statistics*, *79*(4), 527–539.

Barbieri, P., Cutuli, G., & Scherer, S. (2018). *In-work poverty in un mercato del lavoro duale: Individualizzazione riflessiva dei rischi sociali o stratificazione della diseguaglianza sociale? Stato e mercato*, *38*(3), 419–460.

Bargain, O., & Doorley, K. (2011). *Caught in the trap? welfare's disincentive and the labor supply of single men. Journal of Public Economics*, *95*(9-10), 1096–1110.

Bargain, O., Immervoll, H., & Viitamaki, H. (2012). *No claim, no pain. measuring the non-take-up of social assistance using register data. The Journal of Economic Inequality*, *10*(3), 375–395.

Barten, A. P. (1969). *Maximum likelihood estimation of a complete system of demand equations. European Economic Review*, *1*, 7–73.

Becker, G. S. (1981). *A treatise on the family.* Harvard University Press.

Belaïd, F., Ben Youssef, A., & Lazaric, N. (2020). *Scrutinizing the direct rebound effect for french households using quantile regression and data from an original survey. Ecological Economics*, *176*, 106755.

Bernheim, B. D., Schleifer, A., & Summers, L. H. (1985). *The strategic bequest motive. Journal of Political Economy*, *93*(6), 1045–1076.

Bernheim, B. D., Skinner, J., & Weinberg, S. (2001). *What accounts for the variation in retirement wealth among us households? American Economic Review*, *91*(4), 832–857.

Bhargava, S., & Manoli, D. (2015). *Psychological frictions and the incomplete take-up of social benefits: Evidence from an irs field experiment. American Economic Review*, *105*(11), 3489–3529.

Bilbiie, F. O. (2008). *Limited asset markets participation, monetary policy and (inverted) aggregate demand logic. Journal of Economic Theory*, *140*(1), 162–196.

Blundell, R. W., Browning, M., & Crawford, I. A. (2003). *Nonparametric engel curves and revealed preference. Econometrica*, *71*(1), 205–240.

Blundell, R. W., Pistaferri, L., & Preston, I. (2008). *Consumption inequality and partial insurance. American Economic Review*, *98*(5), 1887–1921.

Blundell, R. W., & Stoker, T. M. (1999). *Consumption and the timing of income risk. European Economic Review*, *43*, 475–507.

Blundell, R. W., & Stoker, T. M. (2005). *Heterogeneity and aggregation. Journal of Economic Literature*, *43*(2), 347–391.

Bobasu, A., Dobrew, M., & Repele, A. (2025). *Energy price shocks, monetary policy and inequality. European Economic Review*, *175*, 104986.

Bodkin, R. (1959). *Windfall income and consumption. The American Economic Review*, *49*(4), 602–614.

Borgen, N. T., Haupt, A., & Wiborg, Ø. N. (2022). *A new framework for estimation of unconditional quantile treatment effects: The residualized quantile regression (rqr) model. SocArXiv Papers.*

Brewer, M., & Tasseva, I. V. (2021). *Did the uk policy response to covid-19 protect household incomes? The Journal of Economic Inequality*, *19*(3), 433–458.

Browning, M., & Crossley, T. F. (2001). *The life-cycle model of consumption and saving. Journal of Economic Perspectives*, *15*(3), 3–22.

Bunn, P., Roux, J. L., Reinold, K., & Surico, P. (2018). *The consumption response to positive and negative income shocks. Journal of Monetary Economics*, *96*, 1–15.

Busilacchi, G., & Fabbri, A. (2024). *Does the unemployment trap still exist? the case of the italian minimum income scheme. Social Policy Administration*, *58*(5), 750–770.

Caceres, C. (2019, May). *Analyzing the effects of financial and housing wealth on consumption using micro data* (IMF Working Papers No. 2019/115). International Monetary Fund.

Caliendo, M., & Kopeinig, S. (2008). *Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys*, *22*(1), 31–72.

Campbell, J. Y., & Cocco, J. F. (2007). *How do house prices affect consumption? evidence from micro data. Journal of Monetary Economics*, *54*(3), 591–621.

Cantillon, B., Parolin, Z., & Collado, D. (2020). *A glass ceiling on poverty reduction? an empirical investigation into the structural constraints on minimum income protections. Journal of European Social Policy*, *30*(2), 129–143.

Cantò, O., Figari, F., Fiorio, C. V., Kuypers, S., Marchal, S., Romaguera-de-la-Cruz, M., Tasseva, I. V., & Verbist, G. (2022). *Welfare resilience at the onset of the covid-19 pandemic in a selection of european countries: Impact on public finance and household incomes. Review of Income and Wealth*, *68*(2), 293–322.

Card, D., Kluve, J., & Weber, A. (2018). *What works? a meta analysis of recent active labor market program evaluations. Journal of the European Economic Association*, *16*(3), 894–931.

Carroll, C. D., & Kimball, M. S. (1996). *On the concavity of the consumption function. Econometrica*, *64*(4), 981–992.

Carroll, C. D., Tokuoka, J. S. K., & White, M. N. (2017). *The distribution of wealth and the marginal propensity to consume. Quantitative Economics*, *8*(3), 977–1020.

Carta, F., & Colonna, F. (2025). *Minimum income and household labour supply* (Working Papers No. 1479). Bank of Italy.

Casalis, A., & Krustev, G. (2020). *Consumption of durable goods in the euro area* (ECB Economic Bulletin No. 5/2020). European Central Bank. United Nations Publication.

Cerqua, A., & Pellegrini, G. (2018). *Are we spending too much to grow? the case of structural funds. Journal of Regional Science*, *58*(3), 535–563.

Chai, A. (2018). *Household consumption patterns and the sectoral composition of growing economies: A review of the interlinkages. Inclusive and Sustainable Industrial Development*, (WP3).

Chai, A., & Moneta, A. (2010). *Retrospectives: Engel curves. Journal of Economic Perspectives*, *24*(1), 225–240.

Chai, A., Rohde, N., & Silber, J. (2015). *Measuring the diversity of household spending patterns. Journal of Economic Surveys*, *29*(3), 423–440.

Chakrabarty, M., & Hildenbrand, W. (2016). *How should engel's law be formulated? The European Journal of the History of Economic Thought*, *23*(5), 743–763.

Checchi, D., Dachille, G. P., & De Paola, M. (2021). *Citizens' income, socio-economic characteristics, and social capital. Politica economica*, *1*, 121–148.

Checchi, D., & Peragine, V. (2010). *Inequality of opportunity in italy. The Journal of Economic Inequality*, *8*(4), 429–450.

Cho, Y., Morley, J., & Singh, A. (2024). *Did marginal propensities to consume change with the housing boom and bust? Journal of Applied Econometrics*, *39*(1), 174–199.

Christelis, D., Georgarakos, D., Jappelli, T., Pistaferri, L., & van Rooij, M. (2019). *Asymmetric consumption effects of transitory income shocks. The Economic Journal*, *129*(622), 2322–2341.

Christensen, L. R., Jorgenson, D. W., & Lau, L. J. (1975). *Transcendental logarithmic utility functions. The American Economic Review*, *65*(3), 367–383.

Ciarini, A., Girardi, S., & Pulignano, V. (2023). Minimum income and active labour market policies: The traps of the work-first approaches. In *Social investment and institutional change* (pp. 37–59). Routledge.

Ciarini, A., Luppi, M., & Sacchi, S. (2022). *Make them work! in-work benefits after the pandemic in the reform of italy's minimum income scheme. Stato e mercato*, *42*(3), 445–477.

Clements, K. W. (2019). *Four laws of consumption. Economic Record*, *95*, 358–385.

Clements, K. W., Mariano, M. J., & Verikios, G. (2022). *Expenditure patterns, heterogeneity, and long-term structural change. Economic Modelling*, *113*, 105888.

Clements, K. W., & Si, J. (2018). *Engel's law, diet diversity, and the quality of food consumption. American Journal of Agricultural Economics*, *100*(1), 1–22.

Cobb, C. W., & Douglas, P. H. (1928). *A theory of production. The American Economic Review*, *18*(1), 139–165.

Coglianese, J., Davis, L. W., Kilian, L., & Stock, J. H. (2017). *Anticipation, tax avoidance, and the price elasticity of gasoline demand. Journal of Applied Econometrics*, *32*(1), 1–15.

Comin, D., Lashkari, D., & Mestieri, M. (2021). *Structural change with long-run income and price effects. Econometrica*, *89*(1), 311–374.

Cornelsen, L., Green, R., Turner, R., Dangour, A. D., Shankar, B., Mazzocchi, M., & Smith, R. D. (2015). *What happens to patterns of food consumption when food prices change? evidence from a systematic review and meta-analysis of food price elasticities globally. Health Economics*, *24*(12), 1548–1559.

Cornelsen, L., Mazzocchi, M., Green, R., Dangour, A. D., & Smith, R. D. (2016). *Estimating the relationship between food prices and food consumption - methods matter. Applied Economic Perspectives and Policy*, *38*(3), 546–561.

Corsello, F., & Riggi, M. (2023). *Inflation is not equal for all: The heterogenous effects of energy shocks* (Temi di discussione (Working Paper) No. 1429). Bank of Italy. Bank of Italy.

Croson, R., & Gneezy, U. (2009). *Gender differences in preferences. Journal of Economic Literature*, *47*(2), 448–474.

Curci, N., Grasso, G., Recchia, P., & Savegnago, M. (2020). *Anti-poverty measures in italy: A microsimulation analysis* (Temi di discussione (Economic working papers) No. 1298). Bank of Italy, Economic Research and International Relations Area.

Dachille, G., De Paola, M., & Nisticò, R. (2025). *Guaranteed minimum income and fertility* (DP No. 18105). IZA.

Dao, M., Jirasavetakul, L.-B. F., & Zhou, J. (2024). *Drivers of post-covid private consumption in the us* (tech. rep. No. WP/24/128). International Monetary Fund.

De La Rica, S., & Gorjón, L. (2019). *Assessing the impact of a minimum income scheme: The basque country case. SERIEs*, *10*, 251–280.

De Lucia, C., & Meacci, M. (2005). *Does job security matter for consumption? an analysis on italian households. ISAE Working Paper*, (54).

De Vreyer, P., Lambert, S., & Ravallion, M. (2020). *Unpacking household engel curves. NBER WORKING PAPER SERIES*, (WP26850).

Deaton, A. (1985). *Panel data from time-series of cross-sections. Journal of Econometrics*, (30), 109–126.

Deaton, A. (1988). *Quality, quantity, and spatial variation of price. The American Economic Review*, *78*(3), 418–430.

Deaton, A. (1991). *Saving and liquidity constraints. Econometrica*, *59*(5), 1221–1248.

Deaton, A., & Muellbauer, J. (1980). *An almost ideal demand system. The American Economic Review*, *70*(3), 312–326.

Deaton, A., & Paxson, C. (1998). *Economies of scale, household size, and the demand for food. Journal of Political Economy*, *106*(5), 897–930.

Duesenberry, J. S. (1949). *Income, saving and the theory of consumer behavior*. Harvard University Press.

Dustmann, C., & Görlach, J.-S. (2016). *The economics of temporary migrations. Journal of Economic Literature*, *54*(1), 98–136.

ECB. (2020). *Household wealth and consumption in the euro area* (ECB Economic Bulletin No. Issue 1). European Central Bank. European Central Bank.

Edgeworth, F. Y. (1881). *Mathematical psychics: An essay on the application of mathematics to the moral sciences.* Kegan Paul.

Eggers, A. C., Freier, R., Grembi, V., & Nannicini, T. (2018). *Regression discontinuity designs based on population thresholds: Pitfalls and solutions. American Journal of Political Science*, *62*(1), 210–229.

Engel, E. (1857). *"die produktions- und konsumptionverhaltnisse des königreichs sachsen." reprinted in "die lebenkosten belgischer arbeiter-familien fruher und jetzt." International Statistical Institute Bulletin*, *9*, 1–125.

Engel, E. (1895). *Die lebenskosten belgischer arbeiter-familien, früher und jetzt*. C. Heinrich, Dresden.

Engel, J., & Kneip, A. (1996). *Recent approaches to estimating engel curves. Journal of Economics*, *63*(2), 187–212.

Fagereng, A., Holm, M. B., & Natvik, G. J. (2021). *Mpc heterogeneity and household balance sheets. American Economic Journal: Macroeconomics*, *13*(4), 1–54.

Felice, E. (2018). Regional income inequality in italy in the long run (1871-2010): Patterns and determinants. In *The economic development of europe's regions* (pp. 177–203). Routledge.

Figari, F., Fiorio, C., Gandullia, L., & Montorsi, C. (2020). *La resilienza del sistema italiano di protezione sociale all'inizio della crisi covid-19: Evidenze territoriali (the resilience of the italian social protection system at the beginning of covid-19 outbreak: Territorial evidence). Politica economica*, *36*(1), 3–33.

Figari, F., Matsaganis, M., & Sutherland, H. (2013). *Are european social safety nets tight enough? coverage and adequacy of minimum income schemes in 14 eu countries. International Journal of Social Welfare*, *22*(1), 3–14.

Firpo, S., Fortin, N. M., & Lemieux, T. (2009). *Unconditional quantile regression. Econometrica*, *77*(3), 953–973.

Fisher, I. (1892). *Mathematical investigations in the theory of value and prices.* MacMillan.

Fisher, J. D., Johnson, D. S., Smeeding, T. M., & Thompson, J. P. (2020). *Estimating the marginal propensity to consume using the distributions of income, consumption, and wealth. Journal of Macroeconomics*, *65*, 103218.

Foellmi, R., & Zweimüller, J. (2008). *Structural change, engel's consumption cycles and kaldor's facts of economic growth. Journal of Monetary Economics*, *55*(7), 1317–1328.

Frank, R. H. (1985). *Choosing the right pond: Human behavior and the quest for status.* Oxford University Press.

Friedman, M. (1957). *A theory of the consumption function.* Princeton University Press.

Fulvimari, A., Temursho, U., Vaitkeviciute, A., & Weitzel, M. (2023). *Economic and distributional effects of higher energy prices on households in the eu* (Fair Transition Working Papers). European Commission: Directorate-General for Employment, Social Affairs and Inclusion. Publications Office of the European Union.

Gallo, G., & Raitano, M. (2019). *Il reddito di cittadinanza: Una valutazione degli effetti distributivi. Politica Economica / Journal of Economic Policy*, *35*(3), 357–386.

Gallo, G. (2021). *Regional support for the national government: Joint effects of minimum income schemes in italy. Italian Economic Journal*, *7*(1), 149–185.

Gan, L., & Vernon, V. (2003). *Testing the barten model of economies of scale in household consumption: Toward resolving a paradox of deaton and paxson. Journal of Political Economy*, *111*(6), 1361–1377.

Gangl, M. (2006). *Scar effects of unemployment: An assessment of institutional complementarities. American Sociological Review*, *71*(6), 986–1013.

Gao, J., Peng, B., & Smyth, R. (2021). *On income and price elasticities for energy demand: A panel data study. Energy Economics*, *96*, 105168.

Geary, R. C. (1950). *A note on "a constant-utility index of the cost of living". The Review of Economic Studies*, *18*(1), 65–66.

Gertler, P., & Gruber, J. (2002). *Insuring consumption against illness. American Economic Review*, *92*(1), 51–70.

Giuliani, M. (2024). *Did the citizenship income scheme do it? the supposed electoral consequence of a flagship policy. Italian Political Science Review*, *54*, 101–109.

Gorman, W. M. (1961). *On a class of preference fields. Metroeconomica*, *13*(2), 53–56.

Gorman, W. M., & Deaton, A. (1981). Some engel curves. In *Essays in the theory and measurement of consumer behaviour: In honour of sir richard stone* (pp. 7–30). Cambridge University Press.

Gourinchas, P.-O., & Parker, J. A. (2002). *Consumption over the life cycle. Econometrica*, *70*(1), 47–89.

Green, R., Cornelsen, L., Dangour, A. D., Turner, R., Shankar, B., Mazzocchi, M., & Smith, R. D. (2013). *The effect of rising food prices on food consumption: Systematic review with meta-regression. BMJ*, 346:f3703.

Greene, W. H., & Liu, M. ((2020). *Review of difference-in-difference analyses in social sciences: Application in policy test research. Handbook of Financial Econometrics*, *4*, 4259–81.

Grembi, V., Nannicini, T., & Troiano, U. (2016). *Do fiscal rules matter? American Economic Journal: Applied Economics*, *8*(3), 1–30.

Groot, L., Muffels, R., & Verlaat, T. (2019). *Welfare states' social investment strategies and the emergence of dutch experiments on a minimum income guarantee. Social Policy and Society*, *18*(2), 277–287.

Gruber, J. (1997). *The consumption smoothing benefits of unemployment insurance. The American Economic Review*, *87*(1), 192–205.

Guglielminetti, E., & Rondinelli, C. (2024). *Macro and micro consumption drivers in the wake of the covid-19 pandemic. International Journal of Central Banking*, *20*(1), 181–237.

Hahn, R. W., & Metcalfe, R. D. (2021). *Efficiency and equity impacts of energy subsidies. American Economic Review*, *111*(5), 1658–1688.

Hall, R. E., & Mishkin, F. S. (1982). *The sensitivity of consumption to transitory income: Estimates from panel data on households. Econometrica*, *50*(2), 461–481.

Harold, J., Cullinan, J., & Lyons, S. (2017). *The income elasticity of household energy demand: A quantile regression analysis. 49*(54), 5570–5578.

Hastings, J. S., & Shapiro, J. M. (2013). *Fungibility and consumer choice: Evidence from commodity price shocks. The Quarterly Journal of Economics*, *128*(4), 1449–1498.

Heckman, J., Ichimura, H., Smith, J., & Todd, P. (1998). *Characterizing selection bias using experimental data. Econometrica*, *66*(5), 1017–1098.

Heinesen, E., Husted, L., & Rosholm, M. (2013). *The effects of active labour market policies for immigrants receiving social assistance in denmark. IZA Journal of Migration*, *2*(1), 15.

Hemerijck, A. (2017). *The uses of social investment*. Oxford University Press.

Hicks, J. R. (1939). *Value and capital: An inquiry into some fundamental principles of economic theory*. Clarendon Press.

Hicks, J. R. (1956). *A revision of demand theory*. Clarendon Press.

Hirsch, F. (1976). *Social limits to growth*. Harvard University Press.

Hohmeyer, K., & Wolff, J. (2007). *A fistful of euros: Does one-euro-job participation lead means-tested benefit recipients into regular jobs and out of unemployment benefit ii receipt? IAB-Discussion Paper*, (32).

Houthakker, H. S. (1957). *An international comparison of household expenditure patterns, commemorating the centenary of engel's law. Econometrica*, *25*(4), 532–551.

Houthakker, H. S. (1950). *Revealed preference and the utility function. Economica*, *17*(66), 159–174.

Huntington, H. G., Barrios, J. J., & Arora, V. (2019). *Review of key international demand elasticities for major industrializing economies. Energy Policy*, *133*, 110878.

Imbens, G. W. (2004). *Nonparametric estimation of average treatment effects under exogeneity: A review. The Review of Economics and Statistics*, *86*(1), 4–29.

Imbens, G. W., & Rubin, D. B. (2015). *Causal inference for statistics, social, and biomedical sciences*. Cambridge University Press.

Immervoll, H., Kleven, H. J., Kreiner, C. T., & Saez, E. (2007). *Welfare reform in european countries: A microsimulation analysis. Economic Policy*, *22*(50), 493–549.

Immervoll, H., & Pearson, M. (2009). *A good time for making work pay? taking stock of in-work benefits and related measures across the oecd* (tech. rep.). IZA Policy Paper.

Immordino, G., Jappelli, T., & Oliviero, T. (2024). *Consumption and income expectations during covid-19. Review of Economics of the Household*, *22*(1), 95–116.

Immordino, G., Jappelli, T., Oliviero, T., & Zazzaro, A. (2022). *Fear of covid-19 contagion and consumption: Evidence from a survey of italian households. Health Economics*, *31*(3), 496–507.

Jappelli, T. (1990). *Who is credit constrained in the u.s. economy? Quarterly Journal of Economics*, *105*(1), 219–234.

Jappelli, T., & Pagano, M. (1994). *Savings, growth, and liquidity constraints. Quarterly Journal of Economics*, *109*(1), 83–109.

Jappelli, T., & Pistaferri, L. (2006). *Who is credit constrained in the u.s. economy? Quarterly Journal of Economics*, *121*(1), 83–121.

Jappelli, T., & Pistaferri, L. (2010). *The consumption response to income changes. Annual Review of Economics*, *2*, 479–506.

Jappelli, T., & Pistaferri, L. (2014). *Fiscal Policy and MPC Heterogeneity. American Economic Journal: Macroeconomics*, *6*(4), 107–136.

Jappelli, T., & Pistaferri, L. (2020). *Reported mpc and unobserved heterogeneity. American Economic Journal: Economic Policy*, *12*(4), 275–297.

Jensen, R. T., & Miller, N. H. (2008). *Giffen behavior and subsistence consumption. American Economic Review*, *98*(4), 1553–1577.

Jeon, Y., Thompson, W., Miller, J. I., Hoang, H., & Abler, D. (2025). *Revealing fundamental demand parameters: A new theoretically consistent meta-regression approach to us food demand elasticities. Food Policy*, *136*, 102951.

Jessoula, M., Natili, M., & Raitano, M. (2019). *Italy: Implementing the new minimum income scheme* (ESPN - Flash report 2019/35). European Social Policy Network.

Johnson, D. S., Parker, J. A., & Souleles, N. S. (2006). *Household expenditure and the income tax rebates of 2001. American Economic Review*, *96*(5), 1589–1610.

Kahneman, D., & Tversky, A. (1979). *Prospect theory: An analysis of decision under risk. Econometrica*, *47*, 263–291.

Kang, Z. Y., & Vasserman, S. (2025). *Robustness measures for welfare analysis. American Economic Review*, *115*(8), 2449–87.

Kaplan, G., Mitman, K., & Violante, G. L. (2020). *Non-durable consumption and housing net worth in the great recession: Evidence from easily accessible data. Journal of Public Economics*, *189*, 104176.

Kaplan, G., Moll, B., & Violante, G. L. (2018). *Monetary policy according to hank. American Economic Review*, *108*(3), 697–743.

Kaplan, G., & Violante, G. L. (2018). *Microeconomic heterogeneity and macroeconomic shocks. Journal of Economic Perspectives*, *32*(3), 167–194.

Kaplan, G., & Violante, G. L. (2022). *The marginal propensity to consume in heterogeneous-agent models. Annual Review of Economics*, *14*, 747–775.

Kaplan, G., Violante, G. L., & Weidner, J. (2014). *The wealthy hand-to-mouth. Brookings Papers on Economic Activity*, 77–138.

Keynes, J. M. (1936). *The general theory of employment, interest, and money*. Macmillan, London.

Koenker, R. (2005). *Quantile regression*. Cambridge University Press.

Koenker, R., & Bassett, G. J. (1978). *Regression quantiles. Econometrica*, *46*(1), 33–50.

Koenker, R., & Bassett, G. J. (1982). *Robust tests for heteroscedasticity based on regression quantiles. Econometrica*, *50*(1), 43–61.

Krueger, D., Malkov, E., & Perri, F. (2024). *How do households respond to income shocks? Journal of Economic Dynamics and Control*, *168*, 104961.

Krueger, D., Mitman, K., & Perri, F. (2016). *Macroeconomics and household heterogeneity. Handbook of Macroeconomics*, *2*(11), 843–921.

Krueger, D., & Perri, F. (2006). *Does income inequality lead to consumption inequality? evidence and theory. The Review of Economic Studies*, *73*(1), 163–193.

Krusell, P., & Smith, A. (1998). *Income and wealth heterogeneity in the macroeconomy. Journal of Political Economy*, *106*(5), 867–896.

Labandeira, X., Labeaga, J. M., & López-Otero, X. (2012). *Estimation of elasticity price of electricity with incomplete information. Energy Economics*, *34*(3), 627–633.

Labandeira, X., Labeaga, J. M., & López-Otero, X. (2017). *A meta-analysis on the price elasticity of energy demand. Energy Policy*, *102*, 549–568.

Lagravinese, R. (2015). *Economic crisis and rising gaps north-south: Evidence from the italian regions. Cambridge Journal of Regions, Economy and Society*, *8*(2), 331–342.

Laibson, D. (1997). *Golden eggs and hyperbolic discounting. The Quarterly Journal of Economics*, *112*(2), 443–477.

Lechner, M. (2011). *The estimation of causal effects by difference-in-difference methods. Foundations and Trends in Econometrics*, *4*(3), 165–224.

Leser, C. E. V. (1963). *Forms of engel functions. Econometrica*, *31*(4), 694–703.

Lewis, D., Melcangi, D., & Pilossoph, L. (2024). *Latent heterogeneity in the marginal propensity to consume.* (tech. rep.). National Bureau of Economic Research.

Li, N. (2021). *An engel curve for variety. The Review of Economics and Statistics*, *103*(1), 72–87.

Liddle, B., & Huntington, H. (2020). *Revisiting the income elasticity of energy consumption: A heterogeneous, common factor, dynamic oecd non-oecd country panel analysis. The Energy Journal*, *41*(3), 207–230.

Liddle, B., & Huntington, H. (2021). *How prices, income, and weather shape household electricity demand in high-income and middle-income countries. Energy Economics*, *95*, 104995.

Lise, J., & Seitz, S. (2011). *Consumption inequality and intra-household allocations. Review of Economic Studies*, *78*(1), 328–355.

Love, D. A. (2010). *The effect of marital status and spousal characteristics on portfolio choice. Review of Financial Studies*, *23*(1), 385–420.

Maitino, M., Pacini, S., & Sabato, S. (2024). *The employment effects of the italian minimum guaranteed income scheme (reddito di cittadinanza)* (tech. rep.). IRPET.

Maranzano, P., Monturano, G., & Tridico, P. (2025). *The geography of the italian citizenship income: The role of poverty and inequality in determining spatial heterogeneity across the italian municipalities. Italian Economic Journal.*

Marchal, S., Marx, I., & Verbist, G. (2018). Income support policies for the working poor. In *Handbook on in-work poverty* (pp. 213–227). Edward Elgar Publishing.

Marshall, A. (1890). *Principles of economics.* MacMillan.

Marx, I., & Nelson, K. (2013). *Minimum income protection in flux.* Springer.

Meghir, C., & Phillips, D. (2010). *Labour supply and taxes. Dimensions of tax design: The Mirrlees Review*, 202–274.

Menyhért, B. (2022). *The effect of rising energy and consumer prices on household finances, poverty and social exclusion in the eu* (JRC Science for Policy report No. JRC130650). European Commission Joint Research Centre. European Commission.

Mian, A., Rao, K., & Sufi, A. (2013). *Household balance sheets, consumption, and the economic slump. The Quarterly Journal of Economics*, *128*(4), 1687–1726.

Miller, M., & Alberini, A. (2016). *Sensitivity of price elasticity of demand to aggregation, unobserved heterogeneity, price trends, and price endogeneity: Evidence from us data. Energy Policy*, *97*, 235–249.

Misra, K., & Surico, P. (2014). *Consumption, income changes, and heterogeneity: Evidence from two fiscal stimulus programs. American Economic Journal: Macroeconomics*, *6*(4), 84–106.

Modigliani, F., & Brumberg, R. H. (1954). *Utility analysis and the consumption function: An interpretation of cross-section data. Post-Keynesian Economics*, 388–436.

Moffitt, R. (1992). *Incentive effects of the us welfare system: A review. Journal of Economic Literature*, *30*(1), 1–61.

Moneta, A., & Chai, A. (2014). *The evolution of engel curves and its implications for structural change theory. Cambridge journal of economics*, *38*(4), 895–923.

Mussida, C., & Parisi, M. L. (2020). *Features of personal income inequality before and during the crisis: An analysis of italian regions. Regional Studies.*

Nakajima, J. (2020). *The role of household debt heterogeneity on consumption: Evidence from japanese household data. Economic Analysis and Policy*, *65*, 186–197.

Natili, M. (2020). *Worlds of last-resort safety nets? a proposed typology of minimum income schemes in europe. Journal of International and Comparative Social Policy*, *36*(1), 57–75.

Nesti, G., & Graziano, P. (2025). *The impact of policy legacies on the implementation of citizen income in italy: A policy feedback perspective. Review of Policy Research*, *42*, 276–290.

OECD. (2013). Minimum income benefits in oecd countries. In *Oecd employment outlook 2013* (pp. 185–229).

Pacifico, D., Browne, J., Fernandez, R., Immervoll, H., Neumann, D., Thévenot, C., et al. (2018). *Faces of joblessness in italy: A people-centred perspective on employment barriers and policies* (OECD Social, Employment and Migration Working Papers No. 208). OECD Publishing, Paris.

Pareto, V. F. D. (1906). *Manuale di economia politica con una introduzione alla scienza sociale.* Società Editrice Libraria.

Parker, J. A. (1999). *The reaction of household consumption to predictable changes in social security taxes. American Economic Review*, *89*(4), 959–973.

Parker, J. A., Souleles, N. S., Johnson, D. S., & McClelland, R. (2013). *Consumer spending and the economic stimulus payments of 2008. American Economic Review*, *103*(6), 2530–2553.

Pasinetti, L. L. (1981). *Structural change and economic growth. Cambridge University Press.*

Paxson, C. H. (1993). *Consumption and income seasonality in thailand. Journal of Political Economy*, *101*(1), 39–72.

Peersman, G., & Wauters, J. (2024). *Heterogeneous household responses to energy price shocks. Energy Economics*, *132*, 107421.

Priesmann, J., & Praktiknjo, A. (2025). *Estimating short- and long-run price and income elasticities of final energy demand as a function of household income. Energy Policy*, *207*, 114850.

Rodrigues, C. F. (2001). *Anti-poverty effectiveness and efficiency of the guaranteed minimum income programme in portugal* (tech. rep.). CISEP, Lisbon. ISEG-Departamento de Economia.

Rønsen, M., & Skarðhamar, T. (2009). *Do welfare-to-work initiatives work? evidence from an activation programme targeted at social assistance recipients in norway. Journal of European Social Policy*, *19*(1), 61–77.

Rosenbaum, P. R., & Rubin, D. B. (1983). *The central role of the propensity score in observational studies for causal effects. Biometrika*, *70*(1), 41–55.

Roth, J., Sant'Anna, P. H., Bilinski, A., & Poe, J. (2023). *What's trending in difference-in-differences? a synthesis of the recent econometrics literature. Journal of Econometrics*, *235*(2), 2218–2244.

Rubin, D. B. (1977). *Assignment to treatment group on the basis of a covariate. Journal of Educational Statistics*, *2*(1), 1–26.

Sacchi, S., Ciarini, A., Gallo, G., Lodigiani, R., Maino, F., & Raitano, M. (2023). *Sostegno ai poveri: Quale riforma? dal reddito di cittadinanza all'assegno di inclusione: Analisi dell'alleanza contro la povertà in italia.* EGEA.

Samuelson, P. A. (1948). *Foundations of economic analysis. Science and Society*, *13*(1).

Sancho, F. (2024). *Stone-geary meets ces: The properties of an extended linear expenditure system. Journal of Economic Structures*, *13*(1), 10.

Saraceno, C., Benassi, D., & Morlicchio, E. (2020). *Poverty in italy: Features and drivers in a european perspective*. Policy Press.

Schmieder, J. F., & Von Wachter, T. (2016). *The effects of unemployment insurance benefits: New evidence and interpretation. Annual Review of Economics*, *8*(1), 547–581.

Shapiro, M. D., & Slemrod, J. (1995). *Consumer response to the timing of income: Evidence from a change in tax withholding. The American Economic Review*, *85*(1), 274–283.

Shapiro, M. D., & Slemrod, J. (2003). *Consumer response to tax rebates. The American Economic Review*, *93*(1), 381–396.

Shapiro, M. D., & Slemrod, J. (2009). *Did the 2008 tax rebates stimulate spending? The American Economic Review*, *99*(2), 374–379.

Simonnet, V., & Danzin, E. (2014). *L'effet du rsa sur le taux de retour à l'emploi des allocataires. une analyse en double différence selon le nombre et l'age des enfants. Economie et statistique*, *467*(1), 91–116.

Slutsky, E. E. (1915). *Sulla teoria del bilancio del consumatore. Giornale Degli Economisti*, *51*(1), 1–26.

Sologon, D. M., O'Donoghue, C., Kyzyma, I., Loughrey, J., & Linden, J. (2025). *Distributional impact of soaring prices in europe: A cross-national decomposition of inflation's regressivity and progressivity. The Review of Income and Wealth*, *71*(2), e70010.

Souleles, N. S. (1999). *The response of household consumption to income tax refunds. American Economic Review*, *89*(4), 947–958.

Spies-Butcher, B. (2020). *Advancing universalism in neoliberal times? basic income, workfare and the politics of conditionality. Critical Sociology*, *46*(4-5), 589–603.

Stephens, M. J. (2008). *The consumption response to predictable changes in discretionary income: Evidence from the repayment of vehicle loans. The Review of Economics and Statistics*, *90*(2), 241–252.

Stone, R. (1954). *Linear expenditure systems and demand analysis: An application to the pattern of british demand. The Economic Journal*, *64*(255), 511–527.

Stuart, E. A., Huskamp, H. A., Duckworth, K., Simmons, J., Song, Z., Chernew, M. E., & Barry, C. L. (2014). *Using propensity scores in difference-in-differences models to estimate the effects of a policy change. Health Serv. Outcomes Res. Method*, *14*, 166–182.

Terracol, A. (2009). *Guaranteed minimum income and unemployment duration in france. Labour Economics*, *16*(2), 171–182.

Theil, H. (1965). *The information approach to demand analysis. Econometrica*, *33*, 67–87.

Tonutti, G., Bertarelli, G., Giusti, C., & Pratesi, M. (2022). *Disaggregation of poverty indicators by small area methods for assessing the targeting of the "reddito di cittadinanza" national policy in italy. Socio-Economic Planning Sciences*, *82B*(101327).

Trotta, G., Hansen, A. R., & Sommer, S. (2022). *The price elasticity of residential district heating demand: New evidence from a dynamic panel approach. Energy Economics*, *112*, 106163.

UN. (2018). *Classification of individual consumption according to purpose (coicop) 2018* (Statistical Papers No. M/99). Department of Economic and Social Affairs - Statistics Division. United Nations Publication.

Veblen, T. (1899). *The theory of the leisure class: An economic study of institutions.* Macmillan Company.

Vidal Lorda, G., & Villani, D. (2022). *Whom does inflation hurt most?* (DIGCLASS Policy Briefs No. JRC129558). European Commission Joint Research Centre. European Commission.

Walras, L. (1874). *Eléments d'économie politique pure ou théorie de la richesse sociale.* Corbaz Cie.

Wolff, J., & Nivorozhkin, A. (2012). *Start me up: The effectiveness of a self-employment programme for needy unemployed people in germany. Journal of Small Business Entrepreneurship*, *25*(4), 499–518.

Wolpin, K. I. (1982). *A new test of the permanent income hypothesis: The impact of weather on the income and consumption of farm households in india. International Economic Review*, 583–594.

Working, H. (1943). *Statistical laws of family expenditure. Journal of the American Statistical Association*, *38*, 43–56.

Xu, Y., & Carraro, L. (2017). *Minimum income programme and welfare dependency in china. International Journal of Social Welfare*, *26*(2), 141–150.

Acknowledgments

First of all, I would like to thank my supervisor, Prof. Fabio Di Dio, for his patience in receiving me, for his constant support, and for our fruitful ongoing exchange.

I would like to thank the reviewers, Prof. Barbara Annicchiarico and Prof. Roberto Nisticò, for their time spent on generous revisions, insightful comments, and positive feedback.

A special mention goes to all of my co-authors, Andrea Ciarini, Anna Rita Germani, and Alan Ker, as well as the Directorate I of the Department of the Treasury (MEF), particularly Pietro Zoppoli and Susan Battles, for their collaborative work and data provision.

I would also like to acknowledge the Doctoral School in Social Sciences and Economics, as well as all the academic people who helped me along the way, including Massimo Aprea, Viviana Celli, Augusto Cerqua, Roy Cerqueti, Marina Ciampi, Giuseppe De Arcangelis, Emma Galli, Guido Pellegrini, Luca Zamparelli, and everyone who attended the seminars I held.

Last but not least, my deepest gratitude is for all the people who cross the *Aula dottorandi*, because they are - to a greater or smaller extent - the reason why I was able to finalise my PhD thesis, and I think the world is (and could be) a better place. *Forza DiSSEnnati!*

The final acknowledgment is for my family, for their unwavering support over the last nearly three decades. The thesis is also dedicated to them: to my parents for the freedom they granted me and the critical thinking they instilled in me, to all of my grandparents for their boundless love and the study support provided, and to my two little sisters, Irene and Amélie, to whom I wish a bright future and from whom I can learn so much.

Finally, my heartfelt appreciation goes to all those people who have accompanied me on my journey through life and make sure that it is truly meaningful.

Roma, Primavera 2026

Fausto Libero Barberis