A classical approach to the empirical characterization of the share of essentials and its impact on labor supply using long-run Spanish suvery data, 1998-2022

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Abstract

This study examines the evolution of household spending on essential goods and services in Spain from 1998 to 2022, challenging conventional expectations about the effects of economic growth on consumption patterns. Using microdata from the Spanish Household Budget Survey, we identify essential consumption categories through a Bayesian multilevel beta regression model and analyze their share of total household expenditure over time. Despite significant economic fluctuations and overall income growth during this period, we find that the burden of essentials on household budgets remained relatively stable, primarily driven by the prices of food, utilities, and rent outpacing general inflation. This stability is observed across different bundle compositions and income levels, with the poorest households spending up to 80% of their budget on essentials, while the richest spend around 35%. Our results suggest that many families may find their budget space significantly constrained, challenging the notion of economic progress as a monotonic process that uniformly improves living standards. We also find evidence that the share of essentials influences household labor supply decisions, with a 10 percentage point increase in the share associated with a 2.8 percentage point rise in household activity rates. These findings have implications for poverty measurement, labor market dynamics, and our understanding of economic progress in advanced economies. They highlight the need to consider structural changes and relative price movements when assessing improvements in living standards over time.

Keywords: Essential consumption, engel curves, cost-of-living.

JEL classification: D12, E31, R21.

1 Introduction

This paper presents an estimation and characterization of the share of essentials from 1998 to 2022 using microdata from the Spanish Household Budget Survey (ES-HBS). Its purpose is to explore empirically the classical political economy thesis that wage incomes remain close to or at subsistence by examining the degree of correlation of the share of essentials at current and constant prices with the level of real income (Stirati, 1994; Baumol, 1983; Dobb, 1948). Assuming Engel's Law (Chai and Moneta, 2010; Lewbel and Houthakker, 2018; Houthakker, 1992), a stable nominal share of essentials in the face of increasing productivity would imply a systematic deviation of the relative price of basic consumption, which would indicate that meeting the cost of reproduction needs may require an increasingly larger effort from households. The conventional expectation is the exact opposite, namely, as technical progress fuels per capita real income gains, households can spend a lower share of their budgets on essentials (Foellmi and Zweimüller, 2008; Chai and Moneta, 2014; Pasinetti, 1994). This enables households to distribute the remaining discretionary budget according to their individual preferences (Drakopoulos, 1994; Mas-Collel et al., 1995). The cross-sectional and time-series evidence points to a persistent hierarchical organization of preferences irrespective of income growth (Kaus, 2013; De Vreyer et al., 2020; Chai and Moneta, 2013). A crucial implication of a stable share of essentials at current prices is that households' saving and labor supply decisions might be regulated by the minimum income required to make ends meet rather than an abstract trade-off between leisure and consumption (Wagenknecht, 2013). This would carry relevant implications for stratification analysis and the recent literature on global poverty lines (Sullivan et al., 2024; Moatsos, 2021; Allen, 2020, 2017; Reddy and Pogge, 2010; Decerf, 2022; Kumar et al., 2008). Furthermore, I consider the implications of this on labor supply motivated by recent work on the weight of recreation prices on household's work intensity (Kopytov et al., 2023). By considering the effect that variations in the share of essentials can have on labor supply decisions by households, it also aims to contribute to the understanding of the role that inflation heterogeneity at the micro level can have on classical macrodynamics (Shaikh, 2016, ch. 13-15).

To operationalize the notion of subsistence or essential income, the paper introduces two additional constraints to the classical interpretation. Firstly, the notion is conceptualized not only as containing a social component above pure physical sustenance, as in the classics (Shaikh, 2016; Botwinick, 1993; Stirati, 1994), but also as showing no or only weak correlation with higher income levels. I follow Sen in considering that "an absolute approach [to deprivation] in the space of capabilities translates into a relative approach in the space of commodities" (Sen et al., 1987, p. 168). No matter how much more value a similar quantity of food or shelter represents at one point compared to another, it is the absolute possibility of accessing shelter and food that matters to assess consumption deprivation. Secondly, needs are considered socially constrained and generate distinctive aggregate consumption patterns irrespective of the rationality profile of consumers (Shaikh, 2016, ch. 3; Kirman, 1992). Drawing from the well-established literature on Engel's Law (Chai and Moneta, 2010; Lewbel and Houthakker, 2018; Houthakker, 1992; Kaus, 2013), essentials are identified by the negative effect of higher household disposable income or total household final consumption expenditure levels on the demand proportion for each commodity. This strategy parts with any strong normative, physiological or psychological assumptions (Rao and Min, 2018; Işıkara, 2021; Maslow, 1943). From a methodological perspective, the paper considers the established division between measures of poverty, inequality, and income per capita as a hindrance on the analysis of progress against economic deprivation (Krishna Kumar et al., 2020; Milanovic, 2013; Reddy and Pogge, 2010; Shaikh and Ragab, 2007; Sen et al., 1987; Ravallion, 2016). Hence, it advocates shifting the focus towards continuous measures of deprivation as a means to examine the connection between sufficiency and inequality at multiple levels (Moyn, 2018; Jäger and Vargas, 2023). I believe that the study of essentials can contribute to closing this gap.

This investigation is motivated by the public concern about the widening rift between economic growth and living standards in advanced economies (Gruijters et al., 2023; OECD, 2019; Chetty et al., 2017; Glassco and Holguin, 2016; Dobbs et al., 2016; OECD, 2008), which has been primarily articulated around the "crisis of the middle class" seemingly underpinning Western political discontent (Milanović, 2019; Rodrik, 2018; Streeck, 2017). I find that putting all the explanatory weight on the fact that "[m]iddle incomes have indeed barely grown, in both relative and absolute terms in most OECD countries" does not take us far enough, since we have no shortage of evidence showing that, in "parallel, the cost of essential parts of the middle-class lifestyle have increased faster than inflation" (OECD, 2019, p. 13-14). Terms such as "cost of living crisis", "decent living standards", or "living wages" predate the 2021-2023 inflationary episode as instances of a growing concern about the insufficiency of income growth to generate, by itself, a "minimum wage that will provide a satisfactory standard of living" (ILO Committee of Experts, cited in Anker, 2011b, p. 1; see also Argente and Lee, 2020; Rao and Min, 2018; Anker, 2011b). This sits poorly with the utter confidence of the economics mainstream in two centuries of real growth to bring all forms of poverty down. In addition to stagnating disposable income in a moderate growth context, the data shows a detrimental impact of inflation inequality below the median (Ribarsky et al., 2016, Wimer et al. (2022); Jaravel, 2021; Moatsos, 2021; Allen, 2017; Reddy and Minoiu, 2009). In particular, the price of life essentials, such as food, utilities, and shelter, have contributed the most to long-run purchasing power erosion, at the same time that many conveniences, gadgets, and "chip thrills" have had a compensatory effect on household budgets (Kopytov et al., 2023; OECD, 2019; Gordon, 2016; Baumol et al., 2012). In other words, the evolution of living standards in OECD economies seems to be constrained by structural and distributional forces in the form of unequal access to relatively low growth *and* a secular increase in the cost of living (OECD, 2019; Gordon, 2016; Ribarsky et al., 2016; Chai and Moneta, 2010). Whereas the former has enjoyed research prominence, it's my conviction that the latter remains understudied.

Drawing from the literature on Engel curves (Chai and Moneta, 2010; Houthakker, 2018), the paper presents a novel estimation approach to the identification of a bundle of commodities that can be considered "essentials" or "necessities" without relying on normative assumptions. Section 2 presents a classical economics interpretation of essentials and some motivating facts about household consumption in Spain. In particular, I explain what concept of essentials I use, its relevance to classical political economy, and its connection with the classical theory of wage and unemployment (Shaikh, 2016, ch. 14). The data on inflation heterogeneity and the persistence of rank-invariant demand at the quantile level for basic goods, such as food or energy, presents the initial case for a stable share of essentials. Relative prices are shown to move also in a systematic way *against* increasing the affordability of the consumption categories where the lower quintiles spend the most. The empirical strategy proposes to identify essentials by estimating the sign of the effect on consumption demand by movements on the equivalized spending distribution, which is a standard identification strategy in the Engel's Law literature (López-Laborda et al., 2021; De Vreyer et al., 2020; Lewbel and Houthakker, 2018; Kaus, 2013; Chai and Moneta, 2013). Section 3 explains the methodology and sources used in the paper. To do this, I start with the identification strategy in Section 3.1, which includes a review of relevant literature on Engel's curves, and continue with the inferential strategy in Section 3.2. The estimation fits a Bayesian hierarchical beta regression model (McElreath, 2020; Gelman and Hill, 2007) to the first two moments of the distribution of real expenditure shares for 3-digit consumption headings (up to 45 items), where the average household spending is targeted by a combination of fixed and random coefficients to isolate the main effect of total spending on each item's share on the budget. The statistical model is explained in subsection 3.2.1; I discuss the weak statistical identifiability problem of the model in Appendix A. The data comes from the Spanish Household Budget Survey (ES-HBS) or Encuesta de Presupuestos Familiares, produced by the Spanish National Statistical Office (Instituto Nacional de Estadística). The paper focuses on Spain from 1998 to 2022 as a representative case of a country hard-pressed by a significant income shock during the Great Financial Crisis and an inflation rate above the European average for decades on which annual in-detail consumption surveys have been conducted for more than five decades. Section 3.3 provides the necessary information on the sources and the data modifications necessary to arrive at the pseudo-panel estimation, whose technical details and model checks are presented in subsection 3.4.

Section 4 reports the empirical results of the application of the model to the ES-HBS. Section 4.1 characterizes the evolution of the share of essentials at current prices as stationary and, hence, time- and income-level-independent. Conversely, we can observe that the share of essentials at constant prices has experienced a substantial drop from the late 1990s, which lends crucial support to the hypothesis that there is a systematic increase in the relative cost of essentials that can potentially eat some of the real income gains away in terms of their ability to make independent labor supply and saving decisions. Section 4.2 presents an illustrative estimation of the influence of the share of essentials on labor supply. Section 5 discusses the implications for the literature on relative poverty lines, structural change, and classical macrodynamics. I finish the paper in 6 with some conclusions and possible extensions of this topic.

2 A classical economics interpretation of essentials in relation to some stylized facts of household spending

Essentials or necessaries are commodities universally required for any person to meet their basic needs (Vaggi, 2018). In turn, basic needs are those wants that are intrinsically related to a person's reproduction as a human being. The problem is that needs are neither observable nor perfectly generalizable. The mapping between the space of needs and that of goods or commodities changes across individuals and time. The "troubling ambiguity" in speaking of necessaries stems from the lack of a clear-cut identification of the consequences that unmet needs have upon the pursuit of (a given kind of) life (Marshall, 1980, p. 56). From this economic perspective, to merit theoretical compassion we would need to know whether the individual had a choice in not meeting her (most) basic needs. A popular way of simplifying the problem is by reference to "physical subsistence", where essentials are defined as those "forms of behavior that are enforced by very general necessities of life that man shares with other animals" (Schumpeter, 1986, p. 104). The idea of a minimum-of-existence level underpins Malthusian theories of population (Schumpeter, 1986, p. 244), but also the long-run Ricardian theory of wages (Stirati, 1994; Botwinick, 1993). It has been generally associated with classical political economy in the form of an "iron law of wages" (Blaug, 2012; Stirati, 1994), under which workers' incomes "are inevitably driven near some physical subsistence level" by capitalist forces of production (Baumol, 1983).

However, this is insufficient to skew all ambiguities from the definition of essentials, even accounting for observable differences in physical attributes and behaviors, but it can deliver a minimum consensus around "natural" needs as a "fixed threshold in the space of consumption [coinciding with] basic needs satisfaction" (Decerf, 2022, p. 2). Not by chance does the identification of absolute poverty lines draw from this physical definition of a minimum-of-existence (Allen, 2017, 2013). However, as noted by poverty scholars for a long time, while absolute poverty lines according to physical subsistence are convenient to present matters of poverty as fundamentally different from matters of inequality (Krishna Kumar et al., 2020; Milanovic, 2013; Reddy and Pogge, 2010; Shaikh and Ragab, 2007; Sen et al., 1987), they fail to account for clear situations of deprivation that exceed extreme cases of destitution or cases of severe economic exclusion in rich societies (Ravallion, 2016; Reddy and Minoiu, 2007). In other words, "physical subsistence" offers no conceptual groundwork for essentials or necessities in advanced capitalist societies. When there is clear evidence of relative poverty and extreme material deprivation. What we want to retain from subsistence in the definition of essentials is the idea that no one can achieve economic sufficiency without meeting the needs they represent in the space of commodities regardless of the real income level of the society they live in.

The idea that there is a "historical and social component" in the reproduction cost of the worker and their family can already be found in the classics (Foley, 2006; Heller, 1974). For pre-Smithian political economists, "the minimum subsistence consumption was already seen as influenced by the habits and tastes prevailing in different countries and regions" (Stirati, 1994, p. 33). "By necessaries" Adam Smith understood "not only the commodities which are indispensably necessary for the support of life, but whatever the custom of the country renders it indecent for creditable people, even of the lowest order, to be without" (1976, V, ch.II). An opinion shared by Ricardo, who states that the goods entering the subsistence of workers vary "at different times in the same country, and very materially differs in different countries… [as it] depends on the habits and customs of the people" (Ricardo, 1962, p. 96-97). Marx insisted in this idea by stating that the "means of subsistence" that satisfy the worker's "natural needs, such as food, clothing, fuel and housing", which themselves "vary according to the climatic and other physical peculi¬arities of his country", are "products of history", such that "the value of labour-power contains a historical and moral element" (Marx, 1982, p. 275). Although "in a given country at a given period, the average amount of the means of subsistence necessary for the worker is a known datum" (Marx, 1982, p. 275). Notwithstanding this, different living standards can emerge over time as necessary in absolute terms. From a classical political economy perspective, then, needs belong to a social, objective hierarchy of requirements that overdetermines individual choices, whereas individual commodities acting as needs satisfiers vary from society to society, particularly strongly from time to time (Foley, 1986; Dobb, 1948). According to the classics, however, wages, like any other commodity's price, must fluctuate around the "natural" or "normal" reproduction cost of the worker and their family, including the cost of education and training (Botwinick, 1993). If real incomes rise, can wage rates remain "relative in the commodity space" and gravitate around their "natural" or "normal" price at the same time? The idea that there is a "historical and social component" in the reproduction cost of the worker and their family can already be found in the classics (Foley, 2006; Heller, 1974). For pre-Smithian political economists, "the minimum subsistence consumption was already seen as influenced by the habits and tastes prevailing in different countries and regions" (Stirati, 1994, p. 33). "By necessaries" Adam Smith understood "not only the commodities which are indispensably necessary for the support of life, but whatever the custom of the country renders it indecent for creditable people, even of the lowest order, to be without" (1976, V, ch.II). An opinion shared by Ricardo, who states that the goods entering the subsistence of workers vary "at different times in the same country, and very materially differs in different countries… [as it] depends on the habits and customs of the people" (Ricardo, 1962, p. 96-97). Marx insisted in this idea by stating that the "means of subsistence" that satisfy the worker's "natural needs, such as food, clothing, fuel and housing", which themselves "vary according to the climatic and other

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In classical theory, the relationship between employment and profitability is at the core of this process of turbulent equalization of wages around the worker's cost of reproduction. Actual wages paid result from active bargaining between workers and capitalists within the upper and lower constraints of sufficient profits and a minimum standard of living, under which reproduction costs cannot be met (Botwinick, 1993). *Competition among capitalists* ensures that rates of return on regulating capitals tend to equalize (Shaikh, 2016), which indirectly constraints the wage distribution as well (Mokre and Rehm, 2020). Unemployment and mechanization exert downward pressure on wages, whereas demand growth and price competition will have the opposite effect depending on how successful capitalists are in reducing costs through productivity gains (Shaikh, 2016, ch. 14; Marx, 1982, ch. 25). Lower unemployment strengthens the bargaining power of workers and, concomitantly, higher profitability in specific firms or industries increases the space for wage concessions without compromising a competitive profitability level. Conversely, *competition among workers* leads to increasing labor supply in productivity-leading industries and regulating capitals within, and the resulting wage growth would tend to spill over to firms and industries. This does not preclude the dispersion of wages within and across industries. On the contrary, we have sufficient evidence of the persistence of wage inequality due to structural factors, such as the occupational structure or capital intensity in the same way that different industries show different average profit rates (Mokre and Rehm, 2020). The multifaceted action of real competition produces a simultaneous process of wage dispersion and convergence that tends to push the distribution to the right of the scale. In turn, the "growth of the wage rate… eventually ties together all the production sectors", which prevents all firms and workers from "remain[ing] inert in the face of [the] technological progress" (Pasinetti, 1994, p. 46) spurred by real competition and higher wages (Shaikh, 2016). This process shows how the whole wage distribution can drift upwards as accumulation proceeds, but also how the distributional constraints move labor costs along with income growth, which indirectly may affect prices in industries falling behind in the productivity race.

The implication of this process is a relatively constant wage share in the face of a rising real wage rate (Foley, 2006, p. 142), which contradicts the alleged classical prediction of an "ever-increasing decline in the standard of living of the working class" following the continuous rise in the exploitation rate (Mandel, in Marx, 1982, p. 66). From this perspective, and in light of strong real income gains recorded in advanced economies for decades, perhaps the most salient issue for wage theory to address is not the persistence of voluntary unemployment (Stirati, 1994, p. xii), but why is there *not more voluntary unemployment* as foreseen by Keynes in his *Economic prospects of our Grandchildren* (2016). The standard neoclassical interpretation assumes that the trade-off between leisure and consumption regulates labor supply, such that workers continue to crowd the labor market in pursuit of additional present or future consumption. In this world, wages are market-clearing prices and income effects dominate permanently over substitution effects in labor supply decisions. For classical theory, on the contrary, the "relation between the actual and sustainable real wage is… mediated by the [normal] degree of unemployment" (Shaikh, 2016, p. 648) resulting from the "feedback between the wage share, the rate of profit, and the rate of growth" (Shaikh, 2016, p. 660). The bottom line is that these interrelated forces endogenously create a pool of involuntarily unemployed workers or a "reserve army of labor" (Marx, 1982, ch. 25). Therefore, the sustainable real wage will be the "natural" or "normal" price of labor, under which the subsistence wage will fall in most cases.

The existence of a "reserve army of labor" can explain, in principle, the need for workers to sell their labor-power at extremely different income levels. A living standard that was enough to cut some households' supply of labor in the past seems years or decades later to fall below the current reservation wage. An increasing number of contributions have pointed to the persistence of deprivation in the satisfaction of basic needs independently of the level of real incomes across multiple economies, which is often framed in terms of a "crisis of welfare" (Wimer et al., 2022; Ribarsky et al., 2016; OECD, 2019; Jäger and Vargas, 2023) or the "decline" of the middle class in advanced economies (OECD, 2019; Chetty et al., 2017; Dobbs et al., 2016; OECD, 2008). Classical theory accepts that the minimum consumption level changes over time, mostly driven by the social environment (Shaikh, 2016, p. 96). However, this expectation is not discussed and rather treated as a sociological phenomenon in the same way that the classics accepted a "social and historical" element in setting the subsistence level. In practice, this approach functions similarly to Duesenberry's explanation of the long-term stability of the average propensity to consume by the persistence of individual habits or demonstration effects of the keeping-up-with-the-Joneses' type (Palley, 2010; Duesenberry, 1948; Friedman, 1957, chap. 7). Conceptualized this way, it cannot be integrated into the classical theory of wages. Nonetheless, we have recently seen how food, utilities, and shelter are contributing the most to inflation, at the same time that the price of cutting-edge gadgets and "chip thrills" continue to fall (Kopytov et al., 2020; Baumol et al., 2012). The persistence of high-cost essentials in advanced economies suggests that there are reasons to challenge the mainstream belief in the power of technical progress and product innovations to put necessities on the decline in households' shopping priorities (Chai and Moneta, 2010; Pasinetti, 1994; Houthakker, 1992). Thus, increasing their ability to make independent choices about work, leisure, and consumption. These circumstances suggest that we might benefit from examining changes to the relative price of essentials as a possible force behind the stickiness of voluntary unemployment and the apparent stagnation of economic progress (OECD, 2019; Chetty et al., 2017; Dobbs et al., 2016; OECD, 2008). If we take seriously the possibility that material living standards are not evolving following real income per capita and that inequality may not suffice to explain this gap, then we should consider the evolution of the relative price of essentials.

But, can we tell essential and non-essential consumption apart? From the inductive point of view, a metric to characterize living standards in terms of "necessities" or "essentials" is necessary. Unfortunately, needs cannot be observed directly. To avoid normative assumptions, the traditional approach has relied on identifying regular spending patterns as a function of different measures of resources to approximate needs (Rao and Min, 2018; Işıkara, 2021; Pattanaik et al., 2012). Since Engel (1857), we know that consumption choices are fundamentally hierarchical and respond primarily to equivalized income per capita variations. According to Chai and Moneta (2013, p. 35), Engel sought to exploit the evidence provided by demand curves to "shed light on… living standards" as measured by the number and degree to which consumption can satisfy basic human needs (Stigler, 1954, p. 102), such that the "poorer the individual, a family, or a people, the greater must be the percentage of the income necessary for the maintenance of physical sustenance" (Engel, quoted in Zimmerman, 1932, p. 82). Engel's "law," formalized by Working (1943) and Leser (1963), states that the expenditure share on necessities is an inverse, non-linear function of total expenditure (Chai and Moneta, 2010; Deaton, 1997; Lewbel and Houthakker, 2018). This cross-sectional relationship, other factors such as relative prices, personal tastes, cultural preferences, or family size being equal (Anker, 2011a; Kaus, 2013), "is the best measure of the material standard of living of a population" (Engel, quoted in Zimmerman, 1932, p. 80). Starting with Houthakker (1957, p. 539), the accumulated evidence shows that Engel's relationship is a robust empirical pattern that qualifies as a stylized fact of consumption demand (Houthakker, 1992; Kaus, 2013), with a large number of contributions since validating the results and expanding on the methodology (see, for instance, Aitchison and Brown, 1954; Iyengar, 1967; Muellbauer, 1974a; Deaton and Muellbauer, 1980b; Aasness and Rødseth, 1983; Houthakker, 1992; Holcomb et al., 1995).

Engel's time-series hypothesis, on the other hand, predicts a decline in the weight of necessities on family budgets not only as a function of the position of the household in the income distribution but also as a function of the level of real income. Unlike the cross-sectional hypothesis, the empirical evidence for this decline is weaker and sensitive to contextual factors. Even in the case of food consumption, the expenditure share declines after an income threshold (Kaus, 2013), but it does not completely collapse and even reverses at several points (Gordon, 2016). Figure 1 shows that the evolution of the relative price of broad groups of consumption purposes vary *persistently* apart. Although this refers to Spanish data, it is remarkable how universal those patterns seem to be (Baumol et al., 2012). We can see that personal services, as well as goods with very inelastic demand, such as food and beverages, housing and utilities, education, transportation, hotels and restaurants, tend to become relatively more expensive in a systematic way, whereas the opposite occurs with communications, some leisure goods and services, apparel, furniture and home supplies (Nordhaus, 2006; Raa and Schettkat, 2001).

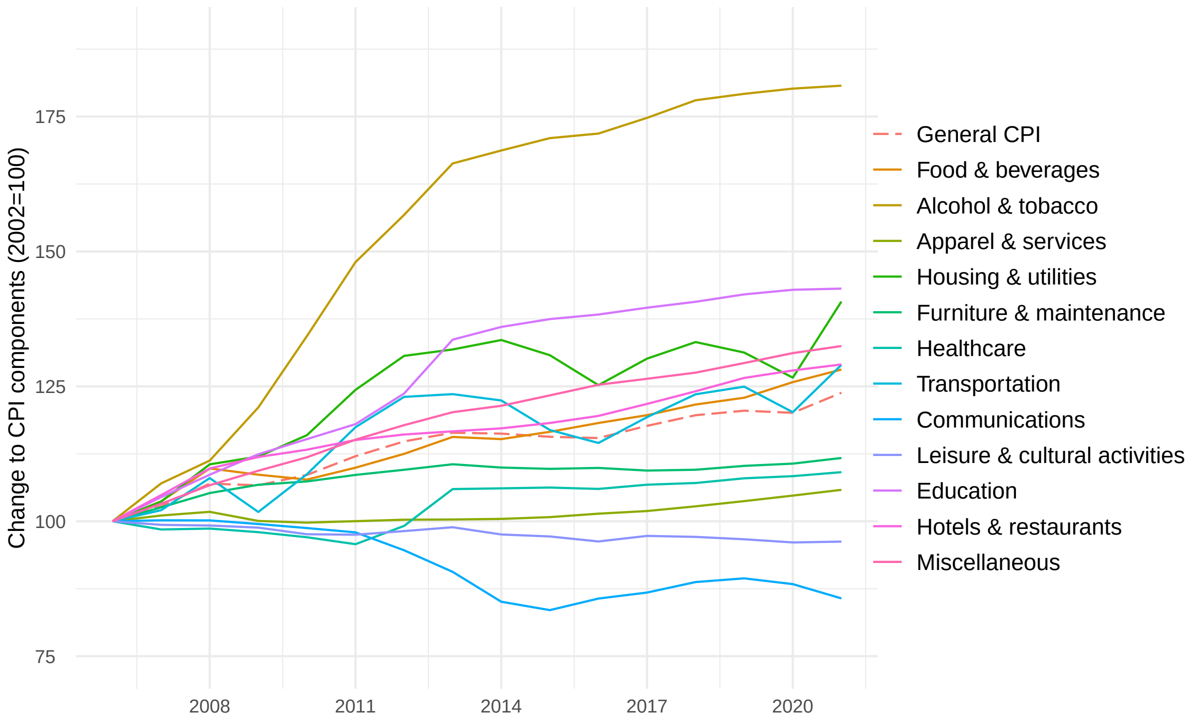

Figure 1: Change to CPI components, 2002-206 (2002=100). *Source*: Author's calculations based on ES-HBS data.

This calls into question the expectation that structural change and the nature of needs are orthogonal (Foellmi and Zweimüller, 2008; Chai and Moneta, 2014) such that the life cycle of any product follows a sigmoidal pattern going from luxury to necessary as measured by their decreasing share on an expanding level of total income or consumption (Pasinetti, 1994; Chai and Moneta, 2013). This leads to the weakening of the idea that poverty declines with income or, conversely, that income growth inevitably raises living standards and the "freedom to choose." This has implications for the analysis of poverty and purchasing power parity in that comparisons across countries should reconcile measures of central tendency for income with consumption composition to approach a representative living standard (Reddy and Minoiu, 2007; Pattanaik et al., 2012). What is difficult to assume is that preferences could be strongly hierarchical and closely dependent on the income distribution position but, simultaneously, inimical to changes in the income level. The expectation in traditional theory is that once basic needs are satisfied and the demand for "necessities" is saturated, consumption choices should gain independence and become influenced by changes in relative prices in addition to income (Drakopoulos, 1994; Mas-Collel et al., 1995). For this to happen, either the price or the appeal of "necessities" would need to grow with income. As will be shown, the available evidence contests the time-series hypothesis by showing that the share of essentials on Spanish household budgets has remained stable, or even worsened, despite the growth in real incomes. Neither the credit bubble of the 2000s nor the Great Financial Crisis and ensuing depression moved significantly the level of this share at current prices.

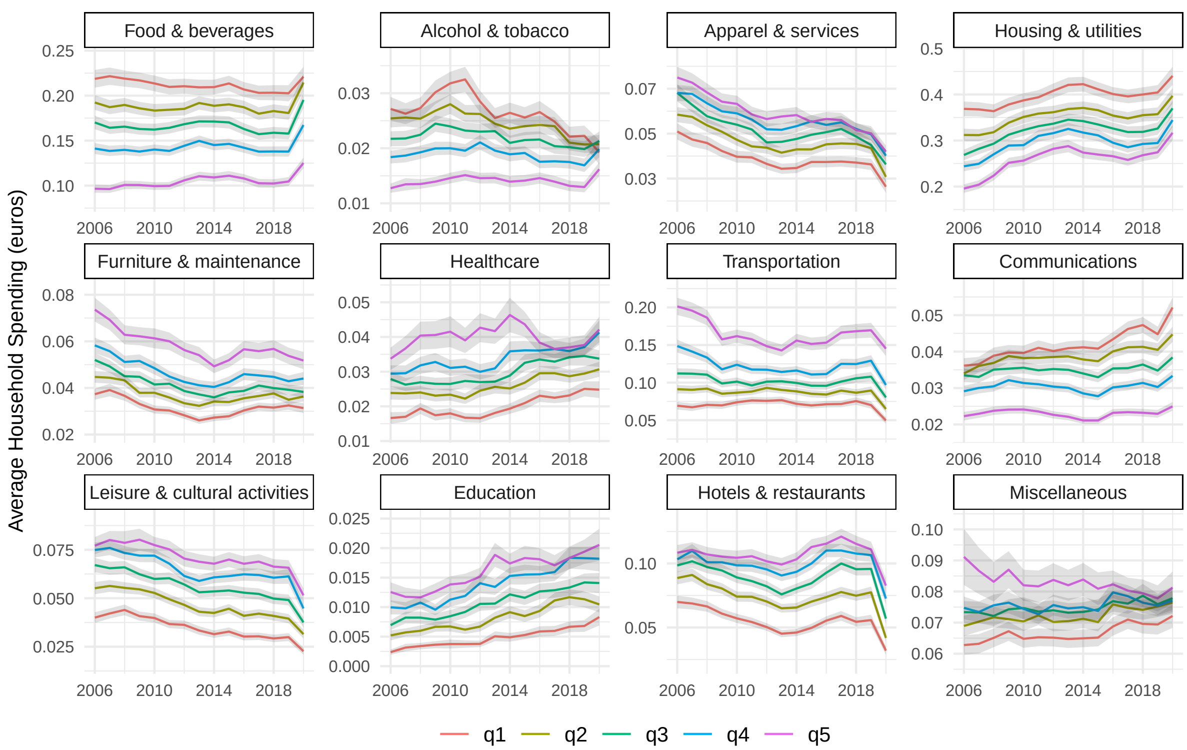

Figure 2: Household spending share on major consumption groups by quntile, 2006-2020. *Source*: Author's calculations based on ES-HBS data.

These patterns are consistent with the literature on tertiarization, which has insisted on the shift to personal services as the defining feature of structural change in the last three to four decades in advanced economies (Raa and Schettkat, 2001; Baumol et al., 2012). Figure 2 shows expenditure shares by equivalized spending quintile. We can see that the bottom 20% spends the most on food, beverages, housing, and utilities. They also seem to be ahead on alcohol and tobacco, as well as communication equipment and services, which the literature has linked to the fall in the price of digital recreation products (Kopytov et al., 2023). Importantly, spending on each category seems to be rank invariant across time and expenditure groups, such that we could broadly

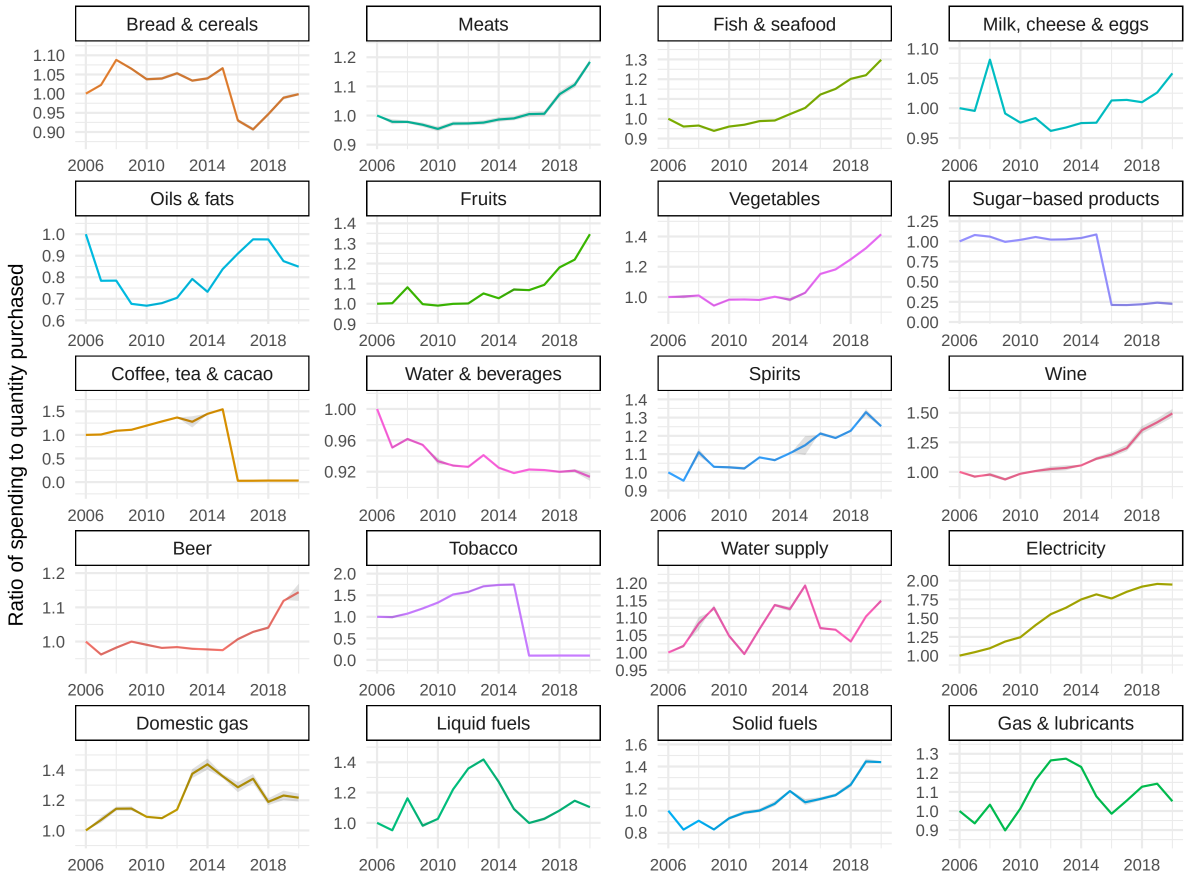

Figure 3: Ratio of average spending to average quantity (4-digits), 2006-2021. *Source*: Author's calculations based on ES-HBS data.

identify expenditure groups by knowing the quintile ranking. The miscellaneous category is the only exception. Finally, the time-invariance of most series is worth noting, particularly about those headings on which the bottom 20% spends relatively more. Apparel and related services, leisure and cultural activities, and possibly furniture and maintenance are on a downward trend. In contrast, households seem willing to spend relatively more on education, housing, and healthcare irrespective of their equivalized expenditure quintile. Even at a more granular level, we can see in Figure 3 that at a 5-digit disaggregation level, many food items are experiencing a growth in the spending-to-quantity ratio. Although quality change is notoriously difficult to capture (Gibson et al., 2016; Stiglitz et al., 2009; Boskin et al., 1996), this might be a reasonable approximation to granular inflation dynamics to illustrate the generality of the pattern shown in Figure 1. At a fundamental level, it lends additional credit to the hypothesis that price inflation is affecting essential goods and services differentially more than some luxuries, which suggests that the analysis of living standards, as measured by real consumption expenditures, is necessary to understand the evolution of well-being in advanced economies, particularly Spain.

In this sense, the price of essentials can play a *structural* and *endogenous* role in the stabilization of the unemployment rate by affecting the labor supply, particularly at the bottom of the wage distribution. In other words, despite real income growth across advanced economies, an approximately constant portion of the worker's wage is necessarily spent on satisfying its basic needs. No matter how much food or shelter quality improves with the historical rise of real output, the purchasing power required to *access* those necessities would tend to remain sufficiently constant to keep the working population in line with the profit needs of accumulation. Far from an effect of repressive powers or a physical stagnation of productive forces, this interpretation emphasizes the impersonal relationship between the labor supply, the cost of reproduction of labor-power, and the profit imperative as driving forces of the relative stability of the share of essentials on working people's budgets. However, the characterization of this relationship as well as the specific channels through which it operates remains understudied.

3 Data and methodology

The preceding section has documented some stylized patterns of consumption spending in Spain since 2006, which lend some credit to three working hypotheses. First, the rank-invariance of spending on certain consumption groups and subheadings testifies to the consistency of the item classification and hints at the hierarchical structure of preferences. Second, the stability of the spending shares and individual prices in most categories indicates that the cost of living in terms of essentials shows no sign of moderation as incomes grow, especially for the bottom 40% of the spending distribution. Third, this bears some potential implications for saving and labor supply decisions. Building on these descriptive results, in this section I seek to positively identify the items that fit into a hypothetical bundle of essential consumption categories. To this end, I first overview the literature on basic needs and Engel curve estimation, followed by the necessary details on the data, the models, and the identification strategy. Finally, I present the estimation results and discuss the statistical limitations involved.

3.1 Identification strategy

To study the evolution of the weight of essentials on household budgets, one would like to have an aggregate metric that could identify the satisfaction of basic needs. Unfortunately, needs of any kind are unobservable, and highly detailed information on domestic spending alongside data on other living conditions is not widely available nor easy to handle statistically. This paper follows the traditional assumption that the hierarchical relationship between spending patterns and income levels can approximate a selection criterion for essentials. To identify a hierarchy of needs, variation in income levels must translate clearly into predictable spending patterns, such that the budget choices of the poor vis-à-vis the rich are sufficiently general to be considered an indication of consumption priorities. In other words, movements along the income distribution must directly affect spending choices regardless, on average, of other economic and demographic factors. In this context, proper specification of the model, including the choice of the functional form and the selection of adequate controls, is necessary to render the relationship of interest identifiable.

The distinctive feature of Engel curves concerning other demand functions is that spending is explained by variations in total household resources independently of relative prices, which rules out the interplay between substitution and income effects (Taylor, 2010; Wong, 2006). This creates several specification issues that underscore the difficulties involved in the study of this family of demand functions. First, finding an appropriate functional form to represent this relationship has proven controversial (Aitchison and Brown, 1954; Stigler, 1954). Engel curves across very different goods are required to share the same mathematical form and satisfy the additivity criterion across a diverse range of goods and services (Houthakker, 1957). Furthermore, the functional form is assumed to be valid for all positive expenditures and to produce reasonable elasticity values, which do not always hold (Leser, 1963). Bias arising from extreme spending figures is expected to be reduced or eliminated via data transformation or an appropriate instrument. However, the tail of the distribution tends to escape direct linearization (Aitchison and Brown, 1954). In the model, errors must represent individual tastes as differences between average and actual spending decisions, which are assumed to be uniform for all income levels despite often suffering from heteroskedasticity in the real data (Kedir and Girma, 2007). For the neoclassical literature, the connection with a direct or indirect utility function is a priority (Deaton and Muellbauer, 1980a); even if finding Engel functions able to meet the adding-up, the homogeneity, symmetry, and negativity conditions is problematic (Beneito, 2003; Taylor, 2010). Notably, the passage from individual decisions to the reported aggregate patterns assumes the recoverability of individual behavior, which depends on the assumption that the cross-section Engel curves reflect the structure of individual household demand functions accurately (Engel and Kneip, 1996).

To modulate the exponential nature of the data, the traditional, and most commonly used, specification of Engel curves is log-linear (Chai and Moneta, 2010; Houthakker, 1952). Although Engel did not use a regression model in his original work (Chai and Moneta, 2010; Kaus, 2013), the canonical model associated with his law was developed by Working (1943), Leser (1963), and Houthakker (1957). The three differ not so much in the choice of dependent and independent variables (y, x), but in the transformations they apply to obtain a linear relation, $\psi(y)$ and $\phi(x)$. Working's model takes the logarithm of total resources $\phi(x) = log(x)$ but not of the expenditure share $\psi(y) = y_i / \sum y_i$, whereas Leser fits the model in levels $\psi(y) = y_i / \sum y_i$ and $\phi(x) = x$, and Houthakker in logs, $\psi(y) = log(y)$ and $\phi(x) = log(x)$ (Chakrabarty and Hildenbrand, 2016). Drawing from these three original contributions, the canonical specification known as Working-Leser takes the form of a linear regression between the share of expenditure $w_{h[i]}$ on good i and the log of total expenditure x_h of household h,

$$w_{h[i]} = \alpha_0 + \beta_1 log(x_h) + \epsilon_i, \tag{1}$$

where the "law… applies closely for families of every size, of every occupation, and in each type of community studied" (Working, 1943, p. 46). In reviewing the most popular specifications, however, Leser (1963) finds that the share-level specification fails to capture the fundamental nonlinearity in demand for luxuries and necessities and that Working's choice is both more appropriate and correct than substituting the share $w_{h[i]}$ by the natural logarithm of the expenditure on good i, $log\ x_i$. Nonetheless, the log-log model has difficulties dealing with the exponential distribution of extreme values of total expenditure or close to zero expenditure shares on the original scale (Engel and Kneip, 1996). To deal with the tail of the distribution, Banks et al. (1997) proposed to transform the model into a quadratic log-log specification by adding additional higher-order income terms,

$$w_{h[i]} = \alpha_0 + \beta_1 log(x_h) + \beta_2 log(x_h)^2 + \epsilon_i \tag{2}$$

As pointed out by Seale and Regmi (2006), additional specifications seek to conform the estimation of Engel demands to the requirements of ordinal utility theory via the inclusion of price terms, such as the Almost Ideal Demand System of Deaton and Muellbauer (1980a) and the Florida model (Seale et al., 1991). A critical addition in this regard is the multi-stage demand systems, which assume the separability of preferences at higher aggregation levels (Chai and Moneta, 2013). Such systems model price indifference and the lack of substitution effects across broad need categories by fitting subsequent regressions at different degrees of aggregation. For instance, overall food expenditure is estimated first, followed by subheadings, such as pork or beef. At this level, substitution effects are expected to behave as predicted by standard neoclassical demand theory. Incidentally, this procedure also helps with estimation consistency (Kedir and Girma, 2007). Despite these efforts to find the most effective or theory-abiding specification, equation (2) has become the textbook model of Engel curves (Laborda et al., 2016), primarily due to its flexibility in capturing the hierarchical relationship between total resources and the demand for a broad range of luxuries and essentials.

Independently from the functional form and linearization method, the endogeneity problem has kept the literature busy debating on the ignorability requirements and searching for appropriate instruments of total expenditure (Beneito, 2003). Provided that there is no measurement error in the data, the exogeneity assumption for total expenditure depends on the extent to which heterogeneous preference orders are uncorrelated with the changes in individual preferences (Battistin and Nadai, 2015), such that, for instance, dispersion around the strictly hierarchical preference for food is assumed to be orthogonal to the level of consumption. As argued by Houthakker (1952), one way around this assumption is to use total household income as an instrument of total expenditure. Wages and other income variants have been considered in the literature.

Battistin and Nadai (2015) proposes, for instance, the average of lagged wages in both levels and logs and their interaction as valid instruments. Even if mean wages seem not to correlate with unobserved household characteristics and measurement error but only with total expenditure, endogeneity may persist if demand for food is correlated with labor supply, which is a fundamental assumption of any hierarchical interpretation of demand that takes stock of relations of exploitation. The limited availability of expenditure instruments in consumption surveys remains a challenge for the external validity of Engel curve estimation.

Finally, the choice of stratification variables is crucial to eliminate confoundings in the interest of effective identification (Cunningham, 2021). In particular, the literature underscores the importance of controlling for the cost of living differences and household composition (Deaton and Salman, 2002). Provided that households are assumed to face the same prices in the market, and the requirement that commodities are qualitatively homogenous, adjusting for prices makes it possible to identify the quantities or use-values satisfying the same need (Deaton, 1997; Chai and Moneta, 2010). On the other hand, it is crucial to account for differences in family size and composition, which were included already by Engel in his studies (Stigler, 1954). Households are assumed to make collective spending decisions. However, the relevant unit of analysis is the household member corrected by the economies of scale and the differentiated needs of children and the elderly (Deaton et al., 1989). Although there are reasons to suspect that inequality within households is non-ignorable, the difficulty in analyzing intra-household allocation makes it an understudied and often overlooked factor (De Vreyer et al., 2020). Connected to this, the needs of children and older people are consistent with a hierarchy of needs, unlike ethnicity, employment status, or country of origin. Other relevant controls in the literature are relative prices (Almas et al., 2018), for they constrain variation in spending to approximate physical demand when it is reasonable to assume that each household faces the same set of commodity prices (Seale et al., 2012). Additional breakdowns, such as type of community, have also been used in the development literature and were part of the first attempts at estimating the relationship between food consumption and income (Deaton, 1997). However, there is no compelling case for thinking they may induce bias, and the literature has mostly abandoned such controls.

With regards to the choice of stratification variables, instead of engaging in the standard practice of finding the best fit by constraining the effect of Engel's Law to certain subpopulations defined by sociodemographic factors (Chakrabarty and Hildenbrand, 2011), I only consider controls that eliminate variations in preferences that might be correlated with the fundamental satiation patterns (Battistin and Nadai, 2015). I control for the relative size and the economies of scale of the household using the modified OECD equivalence scale, but also for inflation by deflating total household equivalized per capita expenditure. Importantly, as it will be explained in Section 3.3, I control for age, gender, education, and occupation by folding households into fictitious cohorts to create a pseudo-panel.

The share-level model can be summarized as in equation 3,

$$w_{i[h]} = \alpha_i + \beta_i \; x_h + \theta_i \; p_i + \; \mathbf{Z}_h \gamma_i + \epsilon_i, \tag{3}$$

where $w_{h[i]}$ is the expenditure share on commodity i at current prices, x is total household expenditure at constant prices normalized by the social average, p_i is the consumer price index (CPI) for good i, and $\mathbf{Z}_h$ a set of additional sociodemographic controls. In practice, I choose to deflate the spending data directly in the outcome variable and to calculate the equivalized total household expenditure to account for the effect of family size already in the explanatory variable. The following section explains the empirical strategy to model the link function to pass from the linear specification to the non-linear space of the outcome frequency and the distribution of the error terms, ϵ_i.

3.2 Inferential strategy

3.2.1 Model description

Most studies of Engel curves follow a parametric approach to estimation (Engel and Kneip, 1996), with the log-linear specification remaining almost unchanged since the seminal Working-Leser model (Chai and Moneta, 2008). However, the most recent literature has opted for nonparametric and semiparametric approaches to relax the set of strong assumptions on the distribution of budget shares that has dominated the literature for a long time (Lewbel and Houthakker, 2018). To contribute to this shift in the literature in favor of more flexible functional forms and to exploit the hierarchical structure of the data, I choose to run a Bayesian multilevel regression (Gelman et al., 2015; Gelman and Hill, 2007) and to model the nonlinearity at the level of the estimator, not the data, by choosing a suitable likelihood function to work with exponentially distributed data.

The Bayesian approach to statistical inference defines probabilities as the theoretical likelihoods or "degrees of belief" about the frequencies with which outcomes are observed. This implies treating parameters as random variables and the data as a fixed quantity. Drawing from basic probability theory, Baye's rule provides a straightforward way of finding the *posterior* probability distribution $p(\theta|y)$ of a parameter θ given the known value of the data y by multiplying the *prior* probability of parameter θ and the conditional probability distribution $p(y|\theta)$, known as the likelihood function. The latter encapsulates the key distributional assumption on the data-generating process, and the former is our prior knowledge of parameters. Dividing by the marginal distribution $p(y)$ we obtain the posterior density properly, but it suffices with the unnormalized posterior density $p(\theta|y) \propto p(\theta)p(y|\theta)$. This framework offers substantial modeling flexibility, an intuitive interpretation of the uncertainty of the estimation, and, most importantly, a parsimonious way of exploiting prior information (McElreath, 2020). The posterior probability distribution is a weighted average of the likelihood and the prior, where the importance of the prior decreases substantially along with the uncertainty as more data becomes available.

Multilevel models, also known as hierarchical or mixed effects models, are a generalization of regression methods that treat the units of analysis as being clustered into groups whose organization derives from an underlying common distribution. This process can account for multiple levels and group relationships, such that groups may not be related to the units in a narrow hierarchical sense (Gelman et al., 2021). This model balances out the group and the "superpopulation" levels by letting parameters vary between or "learn" from the opposite cases of complete and partial pooling (McElreath, 2020, p. 402), a.k.a "partial pooling". It improves prediction power and attenuates bias in small samples or whenever between-group variation is positive but small, "compromising between the overly noisy within-group estimate and the oversimplified regression estimate that ignores group indicators." (Gelman and Hill, 2007, p. 6; Gelman et al., 2015, ch. 5). Although frequentist multilevel models exist, the advantage of a properly Bayesian device is that it fits the group and population regressions simultaneously to the advantage of more precise estimations of the generative process. As noted in Appendix A, this also comes at a non-trivial computational cost.

The observational data explored in this paper presents three relevant features for inference. The outcome variable is a vector of spending *shares*. This implies that it is bounded to the $[0, 1]$ interval, which excludes the traditional normal or t-distributed likelihoods, but it likewise makes Gamma or Weibull suboptimal. The beta distribution is a continuous probability function of the exponential family defined over the unit interval. It is, furthermore, highly flexible in accommodating very different or extreme frequency distributions. As we find in the data, a beta distribution model is the most appropriate likelihood for an exponential-looking, unit-interval bounded frequency. The only difficulty is that, by construction, the beta distribution cannot take values of 0 and 1, which are excluded from the input data. Following (Ferrari and Cribari-Neto, 2004, p. 801) the beta density function can be parameterized as (4), where $0 < y < 1$ is the outcome variable, $0 < \mu < 1$ identifies the mean, $\phi > 1$ the precision parameter, and Γ is the gamma function.

$$f(y; \mu, \phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} y^{\mu\phi-1}(1-y)^{(1-\mu)\phi-1} \tag{4}$$

On the other hand, the values of the outcome variable add up to one at the household level. Market shares or voting behavior are studies that involve working with "compositional data," data that carries partial information. This means that for N parts, once $N-1$ are known, the remaining N^{th} part can be derived simply by subtracting the sum of the $N-1$ parts to 1. Because the D-components do not lie in the Euclidean space $\mathbb{R}^N$ but within the unit simplex $\mathcal{S}^N$, "classical regression models cannot be used directly" (Morais et al., 2016, p. 2). The predicted values cannot be guaranteed to lie in the unit interval, such that "the drawbacks of linear models for fractional data are analogous to the drawbacks of the linear probability model for binary data" (Papke and Wooldridge, 1996). Choosing an appropriately bounded functional form and nesting observations within household groups makes regression feasible.

Similarly, the exact main predictor's value, i.e., the standardized average equivalized household income, *repeats* several times equal to the number of headings each household reports having to spend or consume any amount. This data structure is known as *repeated measures* or *repeated measurements*. In traditional, "single-level" regressions, it violates the independence assumption and typically causes the underestimation of uncertainty. Bayesian multilevel modeling straightforwardly addresses these two issues.

As in any cross-sectional model, unequal variance bias is a severe issue. It can prevent proper posterior prediction by averaging over groups with uneven variability, which is the case. One way to tackle this problem is to include the variance parameters in the multilevel structure as drawn from a common distribution with hyperparameters estimated from the data (Gelman et al., 2015, p. 399). In most regression analyses, only the location parameter of the outcome distribution is estimated, leaving the rest as *nuisance* parameters. *Distributional* regression models estimate other parameters of the response distribution, such as scale or shape. For multilevel models with large between-group variability, this strategy becomes particularly effective in improving posterior predictive accuracy. In the case of a beta regression with overdispersion, I estimate the location μ and the precision ϕ parameters in the parametrization provided in (4).

$$
\begin{aligned}
y_i|\mu_{j[i]}, \phi_{j[i]} &\sim \textbf{Beta}(\mu_{j[i]}\phi_{j[i]}, (1-\mu_{j[i]})\phi_{j[i]}) && (5)\\
\mathit{logit}^{-1}\left(\mu_{j[i]}\right) &= (\alpha_0 + \alpha_{j[i]}) + (\beta x_i + \beta_{j[i]} x_i) + \ D_{i,k}\theta_k && (6)\\
\mathit{log}\left(\phi_{j[i]}\right) &= \alpha_0^{\phi} + \alpha_{j[i]}^{\phi} && (7)\\
\begin{bmatrix}\alpha_j\\ \beta_j\end{bmatrix} &\sim \textbf{MVNormal}\left(\begin{bmatrix}0\\ 0\end{bmatrix}, \Sigma\right) && (8)\\
\Sigma &= \begin{bmatrix}\sigma_\alpha & 0\\ 0 & \sigma_\beta\end{bmatrix} R \begin{bmatrix}\sigma_\alpha & 0\\ 0 & \sigma_\beta\end{bmatrix} && (9)\\
\alpha_j^{\phi} &\sim \textbf{Normal}(0, \sigma_{\alpha^\phi}) && (10)\\
\alpha, \beta, \theta &\sim \textbf{Normal}(0, 1) && (11)\\
\sigma_\alpha, \sigma_\beta, \sigma_{\alpha^\phi} &\sim \textbf{Student's t}(3, 0, 2.5) && (12)\\
R &\sim \textbf{LKJcorr}(4) && (13)
\end{aligned}
$$

Equations (5) to (13) show the full structure of the model. Equation (5) models the outcome variable y_i as Beta-distributed with parameters $\mu_{j[i]}$ and $\phi_{j[i]}$, where j, for $j = 1, 2, ...J$, and i, for $i = 1, 2, ...N$, represent the subpopulation groups and observations, respectively. Expressions (6) and (7) identify the two linear regressions affecting the parameters of interest. For μ I choose a logit link function to map the $[0, 1]$ domain into $\mathbb{R}$, whereas the log-link is set for ϕ by default in the software. The model is a "varying intercept/varying slope" where we combine population-level α, β and group-level $\alpha_{j[i]}, \beta_{j[i]}$ intercept and slope parameters. The predictor variable x_i is the standardized average equivalized household income. On the other hand, I include a set of population-level ("fixed") controls θ_k and a design matrix D, which contains two binary variables indicating if there are household members over 65 or under 16 years old.

The choice of the prior distributions for all hyperparameters is motivated by my expectation about the generative process, prior predictive simulation, and, importantly, computational efficiency (Gelman et al., 2020). Sometimes I narrow prior distribution to improve convergence whenever it has shown not to affect the estimation. In practice, given that I operate with a vast dataset, the prior distribution has little influence on the posterior distribution, which favors robustness independently of the range allowed by the priors. Following Gelman et al. (2008) and Gelman et al. (2020), I set weakly informative priors on the population-level parameters α, β, θ, which are tested against less informative choices without any meaningful change in the (small) estimated effects. For the covariance matrix, in (9) I follow the literature and set a relatively loose **LKJcorr**(4) prior on R (McElreath, 2020). Finally, I place a standard student's-t distributed prior centered on 0 with 3 degrees of freedom and a standard variation of 2.5 for hyperparameters on the group standard deviation $\sigma_\alpha, \sigma_\beta, \sigma_{\alpha^\phi}$.

3.3 Data description

The statistical analysis exploits the data provided by the Household Budget Survey (*Encuesta de Presupuestos Familiares* or EPF in Spanish), produced by the Spanish National Statistics Institute (INE). The Spanish Household Budget Survey (ES-HBS, henceforth) is a yearly survey comprising around 24,000 households living in the Spanish national territory. It uses a two-stage sampling design with stratification of the first-stage units carried out independently for each primary, NUTS2-level regional unit (Autonomous Community). The survey's main purpose is to gather a representative sample of the annual consumption expenditures and quantities purchased by Spanish households at several levels of aggregation. It also includes information on income and other household socio-demographic characteristics. The ES-HBS is also a crucial input to produce Annual National Accounts data, in particular for the derivation of the national consumption total and the weight structure involved in the computation of the CPI.

The breakdown of the expenditure information is provided in four levels corresponding to two digits (12 categories), three digits (39 categories), four digits (120 categories), and five digits (368 categories). It follows the European Classification of Individual Consumption by Purpose (ECOICOP), which is a modification of the Classification of Individual Consumption by Purpose developed by the United Nations Statistics Division to improve the compatibility between consumption and CPI measurement in the European Union. ECOICOP is a functional classification designed to organize and facilitate the analysis of consumption expenditures by households, non-profit institutions serving households (NPISH), and the general government according to their purpose (United Nations, 2018). The ES-HBS uses a domestic version of the ECOICOP classification to collect expenses, which can be readily adapted to meet the standard COICOP classification. In the actual data, there are a few empty headings for specific years and certain discontinuities in the 2006-2021 series due to the change from the COICOP to the ECOICOP classification in 2016, which affects four- or five-digit groupings.

Table 2 provides the code and definition of each 3-digit category. This is the maximum level of disaggregation used for the inferential analysis. This choice is based on three reasons. Firstly, the differences in the categorization for the data collection phase (ECOICOP/collection) and the standard classification disappear at three digits, facilitating the derivation and presentation of the results at an acceptable analytical cost. Secondly, consistency with the CPI breakdown is almost complete at 3 digits. Finally, the computational cost of dealing with hundreds of headings for around 24,000 households would be impractical and of no relevant benefit given the large sample size.

The unit of analysis of the ES-HBS is the household, although there is socio-demographic information at the individual member level. On the other hand, spending data is reported at current, purchaser's prices and recorded when payment obligations are contracted, except for the different forms of own consumption, salary in kind, etc., where goods are valued at replacement, zero-margin prices. A private household is defined as the "person or group of persons that occupy the same main family dwelling or part of it, and consume and share food or other goods or services which are charged to one single budget," with or without family ties (Instituto Nacional del Estadística, 2006, p. 13). A special case is the imputed rent of dwellings, which follows a combination of subjective and objective valuation. The survey separates monetary spending from spending equivalent of domestically sourced or in-kind consumption, which add up to total spending, in addition to some information on quantities for certain categories. In this paper, unless stated otherwise, I use total spending information. Although not as part of the microfiles, the ES-HBS provides information online on real total spending by 4-digit and 3-digit COICOP categories, from which I derive implicit consumer price deflators which I then apply to 3-digit spending information to obtain real expenditure levels and shares by COICOP category.

The ES-HBS sample covers the period 1998-2022, but for computational reasons and to isolate each methodological break in the survey, I divide the estimation in three sets corresponding to the 1998-2004, 2006-2011, 2012-2015, and 2016-2022 periods. There was no ES-HBS survey conducted in 2005. Details on the estimation results and evaluation are provided in section 3.4. As an example, the sample for 2019 consists of $20,817$ households, $836,232$ observations, and 115 unique consumption headings. To eliminate extreme or unworkable cases, I exclude the few households for which a single category represents over 65% of all spending, when it is not the food and beverages purpose. Additionally, I trim extremely lower spending values, i.e., smaller than $1e-7$, from the deflated expenditure data –there is no instance of lower than $1e-6$ spending at current prices. Lastly, I standardized the value of the income predictor to improve computation and interpretation. The final sample is reduced to $20,398$ households, $800,685$ observations, and 106 unique consumption headings, which implies a reduction of -2%, -4.2%, and -7.8%, respectively.

Figure 4 shows the histogram of the frequency distribution of the outcome variable and the predictor of interest. The former is the real household spending share on each of the 47 items for which there is data -45 after 2004, since the data series for narcotics (COICOP 023) and land taxes (COICOP 047) were discontinued in 2006 and subsequent waves. The frequency shows a recognizable exponential shape marked by a remarkable skewness to the left and a long right-hand tail. This is due to most items representing a small percentage of total household spending. There are undoubtedly several households with peculiar consumption baskets, such that just a few headings concentrate a disproportionate amount of real disposable household income. This stretches the tail of the distribution far to the right and adds noise to the prediction of extreme values. I do not believe this is due to the generative process but to how consumption is reported in some instances, so it is assumed to be a feature of the observation process and not the model itself. The mean of the distribution is 0.026, the median 0.009, and the standard deviation 0.054. The histogram shows the well-known functional shape of the income distribution, characterized by a single mode, a long right-tailed, and the close relationship between mean and spread peculiar to the gamma distribution. The mean of the distribution is 16109, the median 14297, and the standard deviation 9205. To facilitate the running of the model and decrease computation time, I standardized the data by subtracting the mean and dividing the resulting vector by its standard deviation, such that the predictor is centered on zero and its shape normalized.

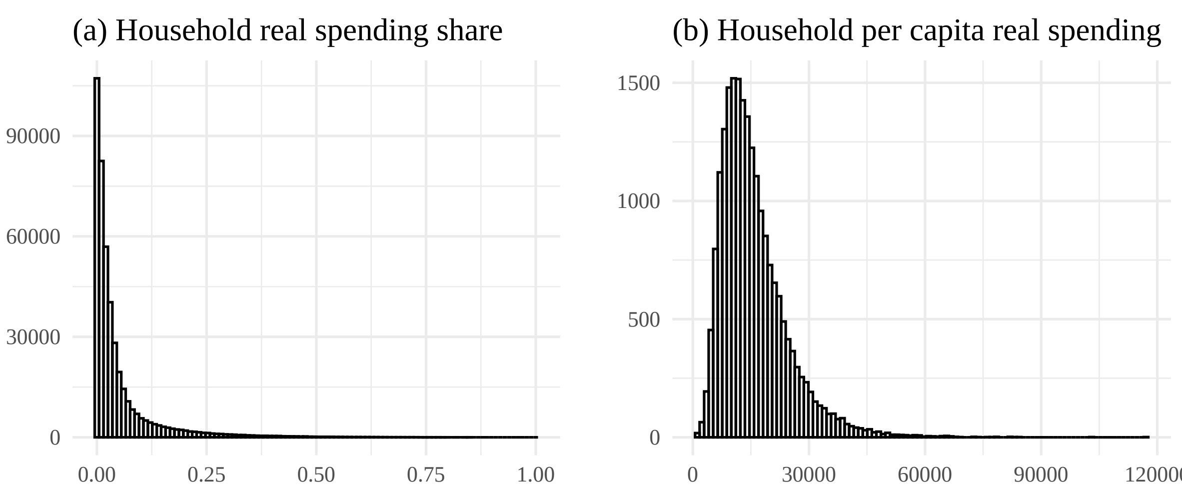

Figure 4: Histogram of the response variable and its main predictor *Source*: Author's calculations based on ES-HBS data.

Due to the computational cost for the estimator to fit the model at 3 digits and for the 24 thousand households each year, I construct a panel of consumer cohorts to reduce the dimensionality of the dataset. To do so I follow the approach to building a "pseudo panel" out of repeated cross-sections developed in Deaton (1985; see Guillerm, 2017; also Verbeek, 2008). Since we have series of cross-sections for a period of up to 23 years, and given that the estimation run-time and precision benefits substantially from a downsized number of observations, it seems convenient to build a panel out of the repeated cross-sections by aggregating the data at the level of fictitious cohorts. These cohorts share a set of characteristics that are time-independent, allowing to track outcomes over time and, by the same token, control for unobserved time-invariant characteristics (Felici et al., 2023). I aggregate grossed-up, household-level spending information based on a a set of socio-demographic characteristics belonging to the reference person of the household: gender (female, male), age (15-34, 35-54, 55-70, +71), education (primary, secondary, tertiary), and 10 occupations corresponding to the main groups in the International Classification of Occupations (ISCO), at 3-digit spending categories (COICOP). Before aggregation, I normalized the weights of the cohorts to ensure that total observations are representative of the population. Through this procedure we obtain 240 ($2x3x5x10$) different cohorts per year. As it is recommended in the literature (Guillerm, 2017; Verbeek, 2008; Gardes et al., 2005), we exclude those cohorts that have less than 50 members, irrespective of whether the number of populated 3-digit spending categories. This constitutes an unbalanced panel of 240 observations per year and 5520 in total.

3.4 Model summary and evaluation

The estimation of the model in equations (5) to (13) is done by posterior simulation using the Hamiltonian Monte Carlo (HMC) algorithm via *Stan* (Team, 2022). See Gelman et al. (2015) for an introduction to Markov Chain Monte Carlo (MCMC) algorithms and Betancourt (2018) for details on the HMC algorithm. The full implementation of the model is done in the *R* programming language by modifying the Stan code prepared by the `brms` package (Bürkner, 2017, 2018) and fitted using the package `cmdstanr`. The model runs 4 Markov chains with 3000 iterations each, of which 1000 are warm-up iterations discarded on (approximate) convergence.

Table 1 reports the estimation summary of the model. It describes crucial statistical features of the posterior distribution of the estimated coefficients. The estimate reports the mean of the distribution, followed by the standard errors. The upper and lower 95% credibility intervals represent the 5% and 95% quantiles of the distribution and have a straightforward probability interpretation. Finally, the split potential scale reduction factor ($\hat{R}$) and the bulk Effective Sample Size (ESS) are the most widely accepted convergence diagnostics (Vehtari et al., 2021). The reported $\hat{R}$ is below 1.01 for every parameter in the model, signaling sufficient convergence. On the other hand, the summary table also shows that the bulk rank-normalized ESS is above the 400 samples recommended (Vehtari et al., 2021, p. 6).

With regards to the point estimates, table 1 reports separately the population-level ("fixed") effects and the group-level ("random") effects. First, the population-level estimates inform about the ability of the model to explain variation at the aggregate level. For instance, it shows that the effect of the main predictor (β) is positive but negligible and highly uncertain, with the mass of the distribution located above zero with a mean 0.01 and a standard error of 0.0048.

		Estimate	Est. error	lw-95%	up-95%	ESS	$\hat{R}$
Model estimated for years 1998 to 2004							
Population-level Effects							
Intercept	α_0	-3.94	0.02	-3.97	-3.90	5080	1.00
phi Intercept	α_0^{ϕ}	6.17	0.01	6.14	6.20	8061	1.00
Expenditure	β	-0.04	0.00	-0.05	-0.03	7225	1.00
Group-level effects (47 levels)							
sd(Intercept)	$\alpha_{j[i]}$	1.18	0.13	0.96	1.46	1627	1.00
sd(Expenditure)	$\beta_{j[i]}$	0.09	0.01	0.07	0.11	1785	1.00
sd(phi Intercept)	$\alpha_{j[i]}^{\phi}$	1.59	0.16	1.31	1.96	1441	1.00
cor(Intercept,Expenditure)	Σ	-0.10	0.14	-0.37	0.17	2953	1.00
sd(year)	$\alpha_{j[i]}^{\tau}$	0.04	0.02	0.02	0.09	2651	1.00
Model estimated for years 2006 to 2010							
Population-level Effects							
Intercept	α_0	-4.09	0.01	-4.11	-4.07	5824	1.00
phi Intercept	α_0^{ϕ}	5.63	0.01	5.61	5.66	8048	1.00
Expenditure	β	0.04	0.01	0.03	0.05	7241	1.00
Group-level effects (46 levels)							
sd(Intercept)	$\alpha_{j[i]}$	1.22	0.13	1.01	1.51	1158	1.00
sd(Expenditure)	$\beta_{j[i]}$	0.19	0.02	0.15	0.24	1355	1.00
sd(phi Intercept)	$\alpha_{j[i]}^{\phi}$	1.34	0.14	1.09	1.65	931	1.01
cor(Intercept,Expenditure)	Σ	-0.23	0.13	-0.48	0.04	1297	1.00
sd(year)	$\alpha_{j[i]}^{\tau}$	0.02	0.01	0.00	0.04	2110	1.00
Model estimated for years 2011 to 2015							
Population-level Effects							
Intercept	α_0	-4.04	0.02	-4.07	-4.01	4923	1.00
phi Intercept	α_0^{ϕ}	5.66	0.01	5.64	5.69	8149	1.00
Expenditure	β	0.06	0.01	0.05	0.07	7571	1.00
Group-level effects (46 levels)							
sd(Intercept)	$\alpha_{j[i]}$	1.18	0.12	0.97	1.44	1512	1.00
sd(Expenditure)	$\beta_{j[i]}$	0.22	0.02	0.18	0.28	1279	1.00
sd(phi Intercept)	$\alpha_{j[i]}^{\phi}$	1.31	0.14	1.07	1.60	1149	1.00
cor(Intercept,Expenditure)	Σ	-0.21	0.13	-0.46	0.05	1732	1.00
sd(year)	$\alpha_{j[i]}^{\tau}$	0.03	0.02	0.01	0.07	2129	1.00
Model estimated for years 2016 to 2022							
Population-level Effects							
Intercept	α_0	-3.69	0.02	-3.72	-3.65	4000	1.00
phiIntercept	α_0^{ϕ}	5.35	0.01	5.33	5.37	8440	1.00
Expenditure	β	0.01	0.00	0.00	0.02	6823	1.00
Group-level effects (45 levels)							
sd(Intercept)	$\alpha_{j[i]}$	1.00	0.11	0.82	1.24	1242	1.00
sd(Expenditure)	$\beta_{j[i]}$	0.18	0.02	0.14	0.22	1373	1.00
sd(phi Intercept)	$\alpha_{j[i]}^{\phi}$	1.51	0.16	1.23	1.85	1299	1.00
cor(Intercept,Expenditure)	Σ	-0.08	0.13	-0.33	0.19	2087	1.00
sd(year)	$\alpha_{j[i]}^{\tau}$	0.04	0.02	0.02	0.09	2112	1.00

Table 1: Summary of the model estimates. *Source*: Author's calculations based on ES-HBS data.

Next, we have the group-level effects, which are the true quantities of interest. They indicate the internal variability across groups. The first thing to notice is the size of the average standard deviation of the intercepts $\alpha_{j[i]}, \alpha^{\phi}_{j[i]}$ and the slope $\beta_{j[i]}$. The standard deviation of both the μ and ϕ group intercepts is rather large at 1 (1) and 1.51 (1.51), respectively. The fact that this variability is not zero indicates that there are clusters in the data that cannot be accurately summarized with an overall coefficient, as it will result from the complete pooling of the data. Conversely, if the estimates were substantially higher, we may consider treating each group as totally independent from one another, so that the best choice would be to run a fixed effects estimation.

By choosing to focus on the "random" effects we assume that we lack sufficient information to follow complete or no pooling at all. In other words, that we can improve our understanding of each group by considering all of them as part of a more extensive process that attenuates the illusion of complete independence. This opens a middle ground between underfitting and overfitting. On the other hand, the mean of the standard deviation of the effect of income on spending shares ($\beta_{j[i]}$) is much more modest at 0.18 (0.18), which means that the estimation borrowed considerable strength from the between-group variability. The variation across intercepts is in no way near the variability among slopes. This tells us that baseline consumption levels differ substantially even if the sensitivity to changes in income is not so radically different across headings. Finally, it is worth noting that I find a sizeable negative correlation among the varying μ intercepts and slopes (Σ) of -0.08 (-0.08) with substantial uncertainty.

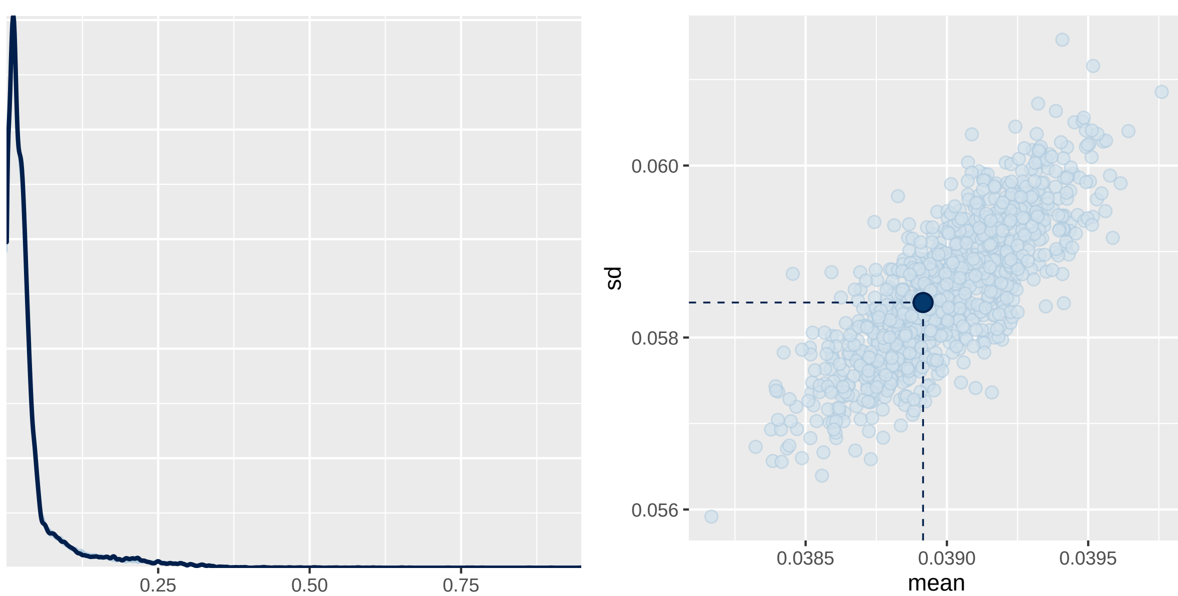

Figure 5: Posterior predictive evaluation. *Source*: Author's calculations based on ES-HBS data.

These results, however, depend on the robustness of the estimation, which demands the evaluation of the posterior distribution. This is a crucial step within the Bayesian workflow, but no unique or standardized approach exists. Perhaps the most helpful test is posterior predictive checking, which allows for the examination of the model's fit to the actual data (Gelman et al., 2020). Figure 5 displays two sets of results. The plot on the left shows the original frequency distribution of the outcome variable with the density overlay of multiple posterior simulations. As shown by the strong overlap, the model can recover the distribution of the independent variable extremely well. Nevertheless, it slightly overestimates the presence of small values and struggles to capture the distribution's tail perfectly. On the opposite side we have the scatterplot of the mean and the standard deviation of 1000 posterior simulations, along with their corresponding sampling mean and standard deviation. This means that the main parameters of the actual data fall within the predictions of the posterior distribution. The only caveat is that the model slightly underestimates the standard deviation.

These posterior predictive tests provide some assurance against gross model misspecification but are not enough to thoroughly evaluate the model. Leave-One-Out Cross Validation (LOO-CV) is a popular model evaluation method that simulates external validity and outlier sensitivity by checking out-of-sample predictive accuracy within the same dataset (Vehtari et al., 2017). The procedure to implement K-fold cross-validation consists of repeatedly partitioning the dataset into a training and a single holdout point to test how well the model can predict each $n-1$ observation based on the rest of the data. This way, we can evaluate the sensitivity of the structure of the model to explain data points, as well as compare competing models. When applied to this model, all Pareto-k estimates are ok (< 0.5), and the Leave One Out Probability Integral Transform (LOO-PIT) fits well most of the data, with some minor, but foreseeable trouble at the end of the distribution.

4 Empirical Results

4.1 Is the weight of essentials constant over time?

This paper argues that answering the question of whether the share of essentials is uncorrelated with the level of income provides a way to study living standards in a different light. This possibility is premised on our ability to separate essentials from non-essentials, including normal goods and luxuries, for each specific cross-section. The criterion of choice is parsimonious and in agreement with the literature: a negative coefficient in response to higher income levels signals that those consumption categories would likely be prioritized in the event of a negative income shock. This method simulates attrition to reveal the hierarchical motivation of consumer choices. Table 2 shows the predicted effect of a shock to the variable of interest equivalent to 60% of the unweighted median (equivalized) household per capita expenditure, approximately €10,000, on the expenditure share for 45 3-digit COICOP items. For illustration purposes, the figure reports only the posterior predictive distribution of the model estimated for the years 2016 to 2022, but as shown in the appendix, results are rather similar across the four pseudo-panel estimations (1998-2004, 2006-2011, 2012-2015, 2016-2022).

Code	Consumption purpose	1998-2004			2006-2010			2011-2015			2016-2022		
		Estimate	Q2.5	Q97.5	Estimate	Q2.5	Q97.5	Estimate	Q2.5	Q97.5	Estimate	Q2.5	Q97.5
011	Food	-0.16	-0.20	-0.13	-0.29	-0.32	-0.25	-0.31	-0.35	-0.27	-0.25	-0.28	-0.23
012	Non-alcoholic beverages	-0.22	-0.27	-0.18	-0.31	-0.35	-0.27	-0.36	-0.40	-0.32	-0.31	-0.35	-0.28
021	Alcoholic beverages	-0.08	-0.10	-0.07	-0.11	-0.13	-0.10	-0.06	-0.07	-0.05	-0.02	-0.02	-0.01
022	Tobacco	-0.24	-0.28	-0.19	-0.40	-0.45	-0.35	-0.46	-0.52	-0.41	-0.49	-0.54	-0.44
031	Clothing	-0.02	-0.02	-0.01	0.03	0.03	0.04	0.02	0.02	0.03	0.00	0.00	0.01
032	Footwear	-0.11	-0.14	-0.09	-0.06	-0.07	-0.05	-0.07	-0.07	-0.06	-0.08	-0.08	-0.07
041	Actual rentals for housing	-0.08	-0.10	-0.06	0.00	-0.01	0.01	-0.02	-0.03	-0.01	-0.08	-0.09	-0.06
042	Imputed rentals for housing	0.01	0.00	0.02	-0.09	-0.10	-0.07	-0.08	-0.09	-0.07	-0.09	-0.10	-0.08
043	Maintenance and repairof dwellings	-0.06	-0.07	-0.04	-0.14	-0.16	-0.12	-0.08	-0.09	-0.06	-0.10	-0.11	-0.09
044	Water supply and dwelling services	0.09	0.06	0.12	0.08	0.07	0.09	0.10	0.09	0.11	0.10	0.09	0.11
045	Electricity, gas and other fuels	-0.05	-0.05	-0.04	-0.19	-0.22	-0.17	-0.19	-0.21	-0.17	-0.21	-0.23	-0.19
051	Furniture and furnishings	-0.04	-0.05	-0.03	0.07	0.06	0.08	0.07	0.06	0.08	-0.04	-0.05	-0.03
052	Household textiles	-0.05	-0.06	-0.04	-0.04	-0.04	-0.03	-0.04	-0.04	-0.03	-0.02	-0.03	-0.01
053	Household appliances	-0.13	-0.15	-0.10	-0.12	-0.13	-0.10	-0.10	-0.11	-0.09	-0.12	-0.14	-0.11
054	Household utensils	-0.02	-0.03	-0.01	-0.05	-0.06	-0.04	-0.02	-0.03	-0.02	-0.05	-0.06	-0.04
055	Housing tools and equipment	-0.13	-0.15	-0.10	-0.09	-0.10	-0.08	0.02	0.01	0.02	-0.05	-0.06	-0.04
056	Routine household maintenance	0.11	0.08	0.14	0.21	0.18	0.24	0.24	0.20	0.27	0.18	0.16	0.20
061	Medical products and equipment	-0.04	-0.05	-0.03	-0.18	-0.21	-0.16	-0.18	-0.20	-0.16	-0.13	-0.15	-0.12
062	Outpatient services	-0.09	-0.10	-0.07	-0.10	-0.11	-0.08	-0.07	-0.08	-0.06	-0.14	-0.16	-0.13
063	Hospital services	-0.22	-0.27	-0.17	0.11	0.09	0.13	0.15	0.12	0.19	0.11	0.09	0.13
071	Purchase of vehicles	-0.04	-0.05	-0.03	0.16	0.14	0.19	0.25	0.22	0.28	0.07	0.06	0.08
072	Personal transport	-0.12	-0.14	-0.10	-0.14	-0.16	-0.12	-0.15	-0.17	-0.13	-0.16	-0.18	-0.14
073	Transport services	0.05	0.03	0.07	0.02	0.02	0.03	0.02	0.02	0.03	0.06	0.05	0.07
081	Postal services	-0.02	-0.04	-0.01	0.18	0.15	0.20	0.21	0.18	0.25	0.11	0.09	0.13
082	Telephone and telefax equipment	-0.15	-0.18	-0.12	-0.08	-0.09	-0.07	0.00	-0.01	0.01	-0.04	-0.04	-0.03
083	Telephone and telefax services	-0.09	-0.10	-0.07	-0.06	-0.07	-0.05	-0.15	-0.17	-0.13	-0.15	-0.17	-0.14
091	Visual and sound equipment	0.02	0.01	0.03	0.04	0.03	0.04	0.05	0.04	0.05	0.02	0.01	0.02
092	Other recreation and culture durables	0.04	0.01	0.07	0.28	0.24	0.33	0.33	0.28	0.38	0.19	0.16	0.21
093	Other recreation spending	-0.12	-0.14	-0.09	-0.04	-0.05	-0.03	-0.07	-0.08	-0.06	-0.05	-0.06	-0.04
094	Cultural services	-0.01	-0.02	0.00	0.02	0.02	0.03	0.02	0.02	0.03	0.01	0.00	0.01
095	Newspapers, books and stationery	0.06	0.04	0.08	0.04	0.04	0.05	0.04	0.04	0.05	0.09	0.08	0.10
096	Package holidays	0.10	0.07	0.13	0.24	0.20	0.27	0.27	0.24	0.31	0.29	0.26	0.33
101	Pre-primary and primary education	-0.01	-0.03	0.00	0.28	0.24	0.33	0.29	0.24	0.33	0.12	0.10	0.14
102	Secondary education	0.06	0.03	0.08	0.26	0.22	0.30	0.35	0.29	0.40	0.22	0.20	0.25
103	Tertiary education	0.00	-0.02	0.01	0.39	0.33	0.46	0.44	0.37	0.51	0.31	0.27	0.34
104	Education not defined by level	-0.05	-0.07	-0.04	0.27	0.23	0.32	0.33	0.28	0.38	0.21	0.18	0.24
111	Catering services	-0.04	-0.05	-0.03	0.06	0.05	0.07	0.09	0.08	0.11	0.08	0.07	0.09
112	Accommodation services	-0.03	-0.05	-0.02	0.34	0.28	0.39	0.41	0.34	0.47	0.29	0.25	0.32
121	Personal care	-0.15	-0.18	-0.12	-0.01	-0.01	0.00	0.00	0.00	0.01	-0.01	-0.01	0.00
123	Other services for personal care	0.01	0.00	0.02	0.01	0.00	0.02	0.11	0.09	0.12	0.07	0.06	0.08
124	Social protection	0.01	-0.01	0.03	0.06	0.04	0.07	0.14	0.12	0.16	0.04	0.02	0.05
125	Insurance	-0.02	-0.03	-0.01	0.02	0.01	0.02	0.03	0.02	0.03	0.05	0.05	0.06
126	Financial services	0.03	0.01	0.04	0.04	0.02	0.07	0.02	0.00	0.05	-0.19	-0.22	-0.17
127	Other services	0.00	-0.02	0.01	0.09	0.07	0.11	0.10	0.09	0.12	-0.08	-0.09	-0.07
128	Remittances fees	-0.02	-0.04	0.00	0.09	0.08	0.11	0.16	0.13	0.18	0.12	0.10	0.14

Table 2: Summary of the coefficient estimates and uncertainty for the four pseudo-panel estimations. *Note*: Row shadowing indicates that a given consumption purpose is an essential across periods. *Source*: author's calculations based on ES-HBS.

From Table 2 we can observe a clear distinction between two clusters, with very few items for which the level of income has no influence, which is a telling sign of the strongly hierarchical organization of consumer choices in society. On the one hand, we see that rent, food, utilities, or medical products feature among the goods and services that households would likely prioritize when their income is lower or, conversely, when they experience a shift towards the right-hand tail of the equivalized expenditure distribution. The selection that emerges from the model is, in fact, very close to the common findings in Engel's Law literature (Chai and Moneta, 2013; Kaus, 2013; Houthakker, 1992), proximate also to some normative understandings of necessities (Işıkara, 2021; Rao and Baer, 2012). Nonetheless, it is also fair to point out that a bunch of categories, such as tobacco or financial services, are "essentials" in the positive sense of being a choice negatively correlated with cross-sectional income levels, but which would be excluded from any reasonable a priori or physiological definition of necessities (UNECE, 2020; Allen, 2017). These results are consistent for most goods and services for the full 1998-2022 period, and the specific bundle from which the totals are calculated comes from the set of categories fitting the definition of essentials for the four panels. In 1998, Spanish households spent on average 43.7% of their budget on necessities, whereas it is 46.1% in 2022. Percentages vary significantly across the distribution of per capita expenditure, where percentiles 1-5 spend close to 80%, and percentile 99 as low as 35% in 2022. Conversely, total spending on "luxuries" was 8.8% in 1998 and 10% in 2022.

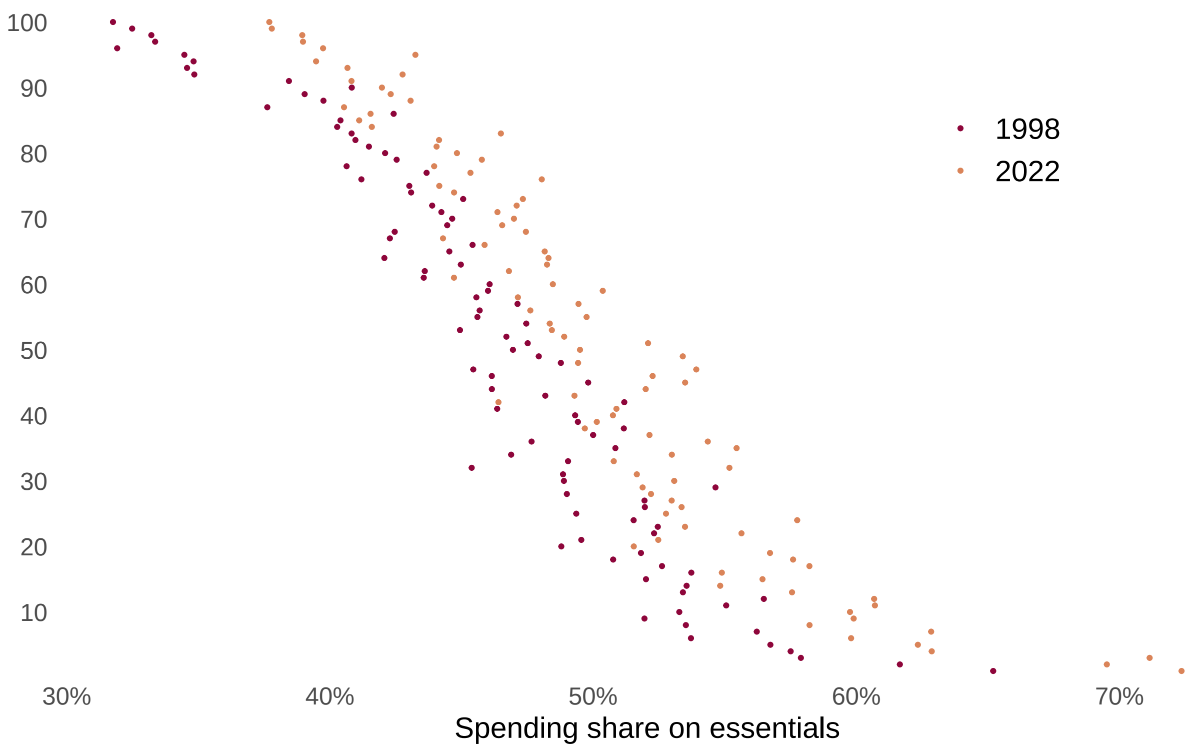

Figure 6: Percentile distribution of per capita spending on essentials in Spain. *Source*: Author's calculations based on ES-HBS data.

The average level, however, conceals large distributional differences. Figure 6 shows the percentile cumulative distribution of the weight of essentials on total household nominal spending for the years at the beginning and the end of the period studied in this paper. This percentage is obtained by aggregating the total expenditure on those consumption categories for which the 95% confidence interval falls clearly below zero in all of the four pseudo-panel estimations. This indicates two important facts. First, the plot conveys neatly the estimation results from Table 2 by showing the relatively smooth distribution of the demand for necessities as we move from the bottom to the top expenditure levels. We can observe that the top decile concentrates about 30% of the total budget spent on headings matching the essentials classification, whereas it reaches close to 70% in the case of the first percentiles. The median stays around 45%. The S-shaped distribution of essentials testifies to the rather stable diffusion forces that link expenditure levels and the demand for certain commodities. Second, the figure reveals that the burden of necessities is larger in 2022 than in 1998, as shown not only by the average spending but by the shift of the whole distribution to the right. It is remarkable to see that almost 25 years of growth in real per capita income seems to have been unable to reduce the burden that the purchase of food, energy, or shelter puts on all budgets, from the first to the last percentile.

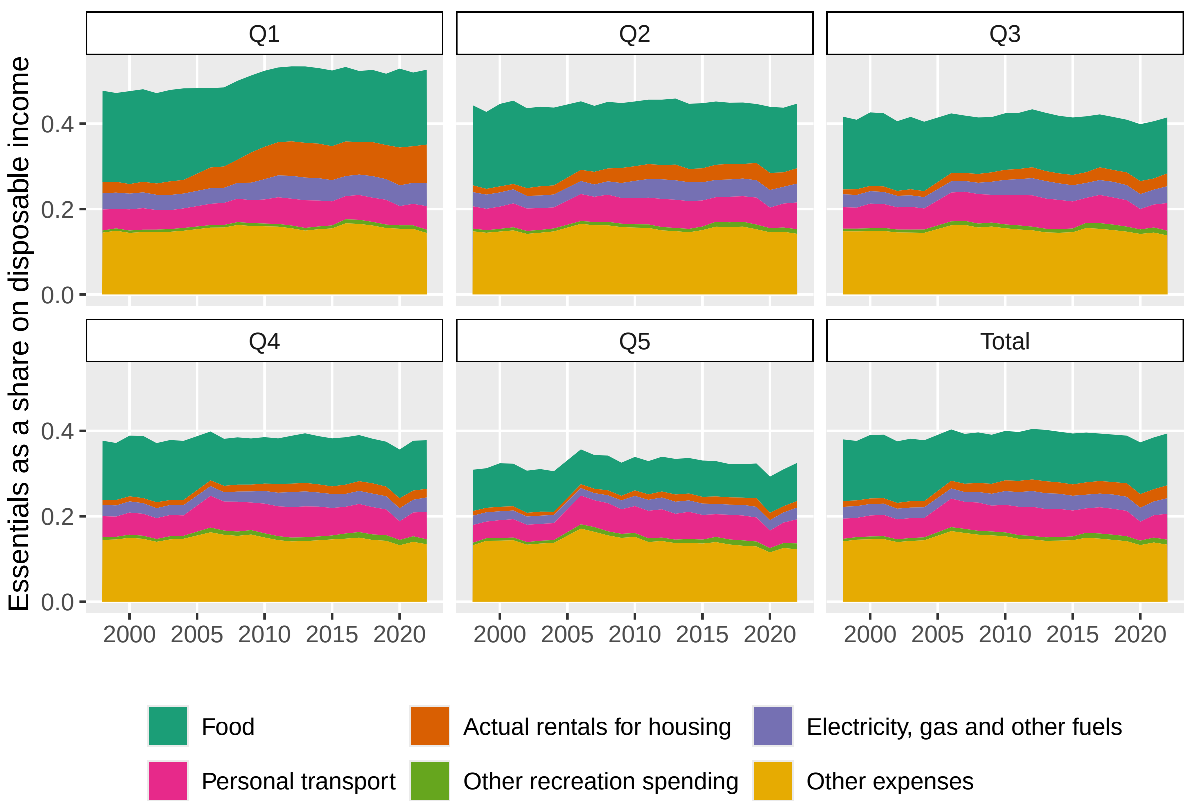

Figure 7: Share of necessities over total consumption spending by quintile *Source*: Author's calculations based on ES-HBS data.

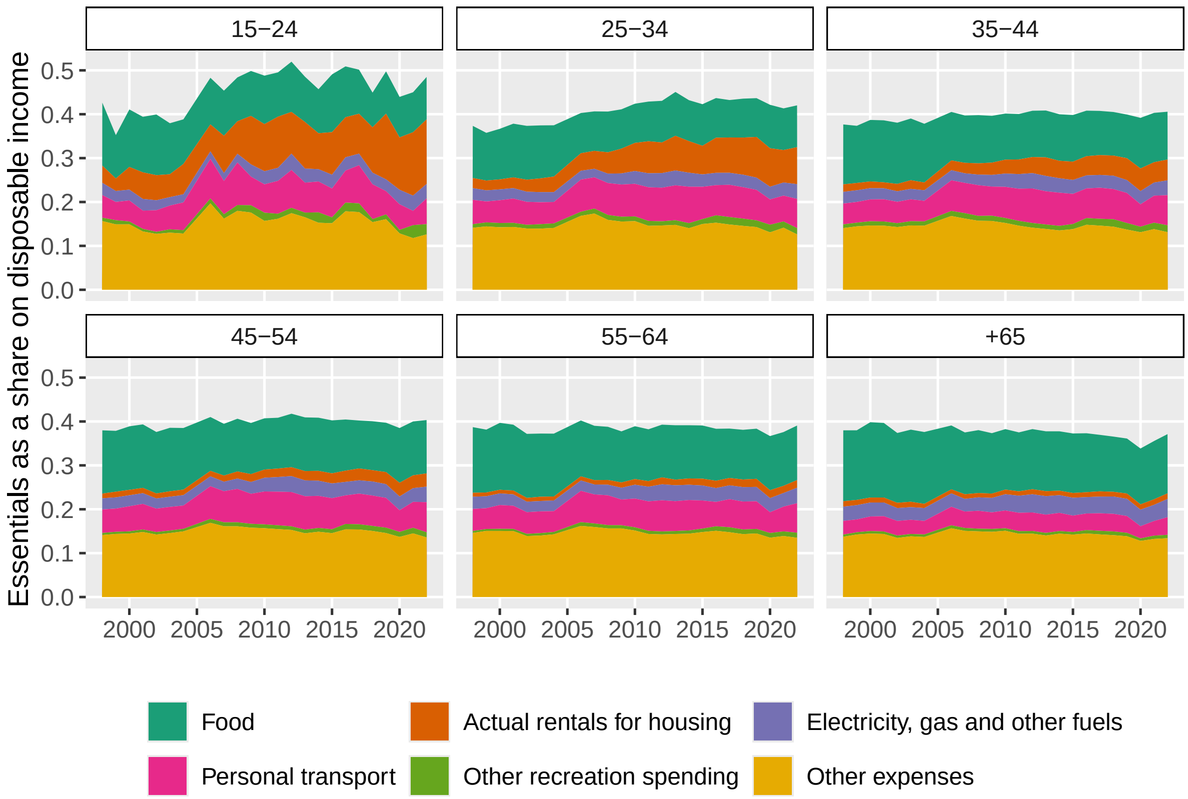

Figure 8: Share of necessities over total consumption spending by age group *Source*: Author's calculations based on ES-HBS data.

To zoom in on the composition of the share of essentials and move beyond a comparison of two cross sections, figure 7 shows the whole time series by quintile, but also breaks down the share into six expenditure components: food, actual rents paid, energy supplies, personal transportation, other recreation expenditures, and other expenses, which collects the remaining consumption purposes. The first thing to notice is the stability of the series, which seems relatively insensitive to the powerful macroeconomic fluctuations that affected the Spanish economy during the middle part of the period. Although marginal, we can detect a timid drop in the share of food expenditures in exchange for a slight increase in spending on electricity, gas, and other fuels. The share of other recreation expenditures, which we might consider a proxy for higher-order needs that according to Engel's Law should progressively monopolize income growth, is only moderately expanding out of a very small percentage. Figure 7 suggests that there are no strong compositional changes that could provide an item-specific explanation for the stability of the share of essentials.

The trends are overall stable but for the poorest. Figure 7 does show that the first quintile has experienced a noticeable increase in the weight of essentials and, hence, a squeeze of their discretionary budget space driven by rent and utilities. As expected, each quintile shows a lower aggregate share, the second and third quintiles have very

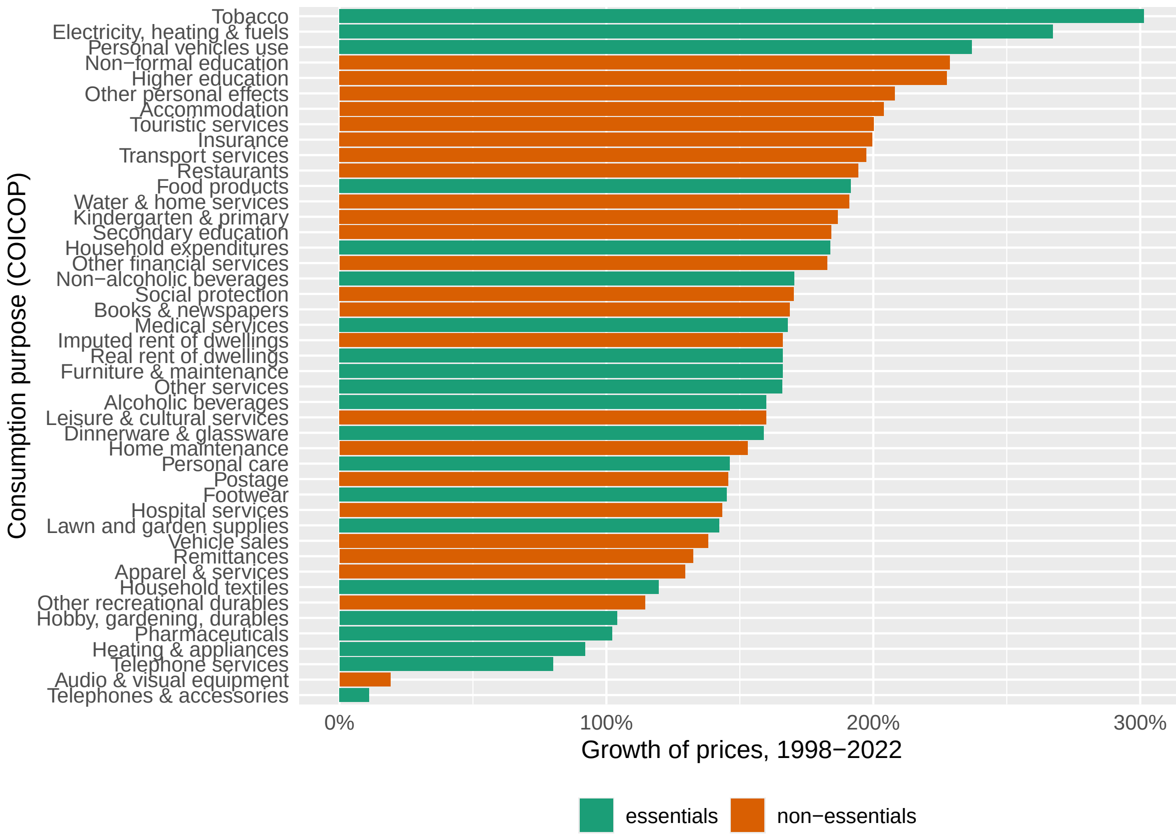

Figure 9: Growth rate of implicit price deflators for 3-digit consumption purposes during the 1998-2022 period. *Source*: Author's calculations based on ES-HBS data.

similar shares and compositions, and it is the last quintile for which we can observe a substantial decline in the share of food, utilities, and rent. As figure 8 suggests, this is not only an income distribution issue, but also closely related to age. It is well-known that an overlap exists between age, income, and wealth accumulation that makes these results relatively unsurprising (Romer, 2012; Deaton, 1997; Carroll and Summers, 1991), at least in connection to tenure. Furthermore, the substantial improvement of pensioners' incomes relative to the youngest cohorts in Spain in combination with a lower propensity to consume situates the extent of the generational gap within the expectations of the literature. What the estimation fails to show is any relevant and long-lasting decline in the weight of essentials or any of their largest subcomponents.

As pointed out in the introduction, this result challenges the time-series prediction of Engel's Law. Since there has been growth and fluctuations of real equivalized income from 1998 to 2022 in Spain, it might be relevant to compare the growth in prices. Figure 9 shows the growth rate of the implicit price deflator for 3-digit consumption purposes. The chart suggests a mixed picture. Whereas fastest growing prices are among essentials, most non-essentials are distributed between the second-fastest growing and the most stable prices. Tobacco, electricity, heating & fuels, and personal vehicles

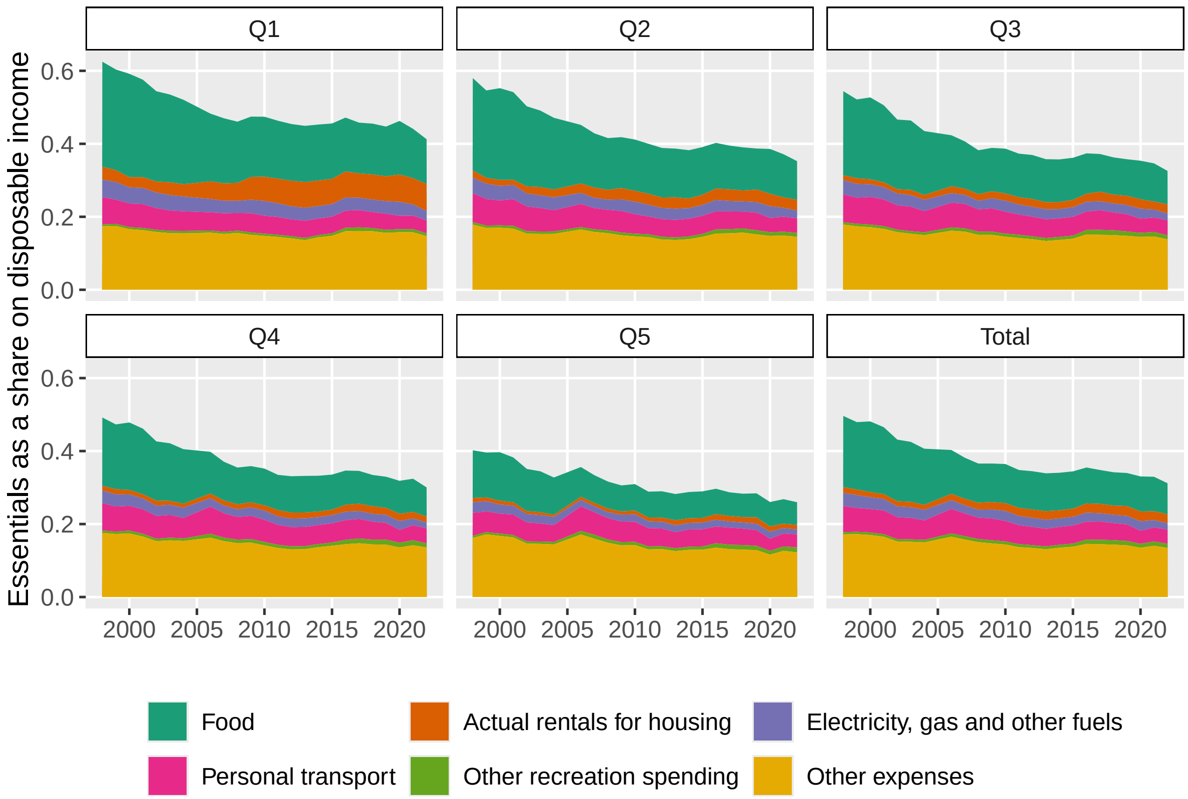

Figure 10: Share of necessities over total deflated consumption spending by quintile
Source: Author's calculations based on ES-HBS data.

use, which are all essentials, are the consumption purposes that have experienced the fastest inflation. Among non-essentials, the top three by price growth are non-formal education, higher education, and other personal effects. Looking at the top groups by their weight on household budgets, the top five groups are imputed rent of dwellings (042), food products (011), restaurants (111), personal vehicles use (072), and electricity, heating & fuels (045), whose prices grew by 166%, 192%, 194%, 237%, and 267%, respectively. We even have prices falling behind general inflation, with pharmaceuticals (061), heating & appliances (053), telephone services (083), audio & visual equipment (091), and telephones & accessories (082) leaving the largest gap. These groups are the ones predicted by the literature (Baumol et al., 2012). But the most relevant feature of this differential price growth is, by implication, the substantial change to relative prices as illustrated in Figure 1. In so far as these changes affect essentials and non-essentials differently, the share of essentials at constant prices could adopt any feasible trend.

Alternatively, we can break down the effect of prices by quintile and main essential spending category. Figure 10 replicates 7 but substituting current by constant expenditures. I deflate each consumption purpose by its price index and income by the general CPI. The comparison between figures 10 and 7 suggests that the stability of the nominal spending share hides away a robust decline in most real spending shares. Most notably, we see the share of food expenditures almost halving for the bottom 60%. Personal transport experienced also some visible decline. The only consumption category going in the opposite direction is actual rents paid, which suggests that the growth in nominal expenditure might not be as dramatic as it seems. Finally, the miscellaneous category of other expenses remained almost unchanged in nominal or real terms. Since price indexes have problems accounting for quality change (Stiglitz et al., 2010; Boskin et al., 1996), we cannot be completely sure that the discrepancy between the nominal and the real shares answers solely to the change in relative prices. Nonetheless, we can recall Figure 3 as circumstantial evidence that many 5-digit food items and utilities were experiencing an unfavorable evolution of the ratio of spending to physical volume.

4.2 Is the price of essentials constraining labor supply?

We can extend our analysis of essentials to the effect that the stability of the nominal share may play over household labor supply and savings decisions. As noted in the introduction, a crucial insight of classical theory is that a large proportion of workers, especially at the bottom of the wage distribution, sell their labor-power as this is the way they can pay to satisfy their basic reproduction needs. In a modern economy, while this idea is generally regarded as inadequate, the evidence on the evolution of the share of essentials presented in Section 4.1 suggests that variations in the relative price of essentials may bear some influence on the activity rate and saving decisions of households. On the one hand, I consider that the activity rate of the household speaks more clearly about the need to increase resources than employment or the number of hours worked, which are also partly determined by the objective conditions of the labor market. On the other, since saving decisions tend to be guided by rules of thumb and precautionary motives than expectations about future consumption (Romer, 2012; Palley, 2010), it is reasonable to think that savings are responsive to positive changes in the share of discretionary spending or, by the same token, to declines in the share of essential spending (Wagenknecht, 2013). However, due to data limitations explained 6, I do not consider savings in this paper.

To examine the weight of essentials on the supply of labor, I ask how the work intensity of the household would, i.e. the percentage of working-age household members that are either employed, on temporary leave, self-employed, or actively searching for a job, change in response to variations in the nominal share of essentials. I apply this linear relation to the full 1998-2022 pseudo-panel. The underlying cross-sections are grouped in cohorts defined by age group, occupation, education level, and gender, as described for the estimation of essentials in Section 3.3 (Deaton, 1985; Guillerm, 2017; Verbeek, 2008). This means that all the variables are cohort averages. To render the relationship identifiable, I control for several variables. First, the log transformation of the total household real disposable income isolates the effect of the share of essentials from cases where real income might decline, effectively correcting for the relationship with the nominal share of essentials. Second, I include the employment rate to control for the relatively high unemployment rate in many segments of the Spanish labor market. Additionally, I include the log transformation of the cohort's occupation wage and employment rate, to neutralize inequality in employment and wages across occupations.

The results of the estimation are presented in Table 3, which reports the estimated effect, the standard error, the 95% credibility intervals, the bulk Effective Sample Size (ESS), and the split potential scale reduction factor ($\hat{R}$). As noted before, the model converges appropriately, and the estimation displays no pathological behavior. The parameter results are divided between those affecting the mean μ, the precision ϕ, and the binary separation between 0 observations and positive ones regulated by parameter α in the zero-inflated expansion of the beta regression. Additionally, we can separate population and group effects, since the model controls for time by using an intercept-only random effects estimation for each year both for μ and ϕ.

	Param.	Estimate	Est. error	lw-95%	up-95%	ESS	$\hat{R}$
Population-level Effects							
Intercept	μ	-0.47	0.61	-1.63	0.72	1578	1.00
phi Intercept	ϕ	1.47	0.20	1.10	1.85	600	1.00
Share of essentials	μ	2.15	0.16	1.84	2.47	2391	1.00
log Expenditure	μ	-0.24	0.04	-0.32	-0.15	2483	1.00
Cohort employment rate	μ	4.69	0.06	4.56	4.81	2701	1.00
log Occup. wage rate	μ	0.09	0.06	-0.02	0.20	2490	1.00
log Occup. employment rate	μ	0.11	0.01	0.09	0.13	2869	1.00
Random time effects (years)							
sd(Intercept)	μ	1.22	0.18	0.93	1.62	529	1.01
sd(phi Intercept)	ϕ	0.98	0.16	0.73	1.33	702	1.00
Binary selection parameter							
binary distribution (0/not 0)	α	0.05	0.00	0.04	0.05	2255	1.00

Table 3: Summary of the pseudo-panel estimates of the effect on the household activity rate. *Note*: The pseudo-panel averages over households within cohorts defined by age group, ocupation, education level, and gender. *Source*: Author's calculations based on ES-HBS data.

The variables of interest are the linear term determining the mean of the distribution. In particular, the main effect is captured by the share of essentials at current prices, which has the expected sign indicating a negative relationship between the affordability of basics and the activity rate of the household. The model is non-linear, so to measure the effect we need to reverse the logit link for μ and the logarithmic link for ϕ. Thus, the average marginal effect of a 10 percentage point increase in the share of essentials is equal to 2.8 points rise of the average household activity rate. This is a significant and credible effect, which supports the hypothesis that the price of essentials can influence labor supply decisions. The correlation with the cohort employment rate is even stronger, but its role in the estimation is to control for labor market conditions. Furthermore, the logarithm of the inflation-corrected value of the cohort-average equivalized household expenditure level is small and negative, which corresponds to our prior expectation about the relationship between this and the outcome variable. I treat the rest as nuisance parameters.

Since it is a nonlinear regression model, the slope changes as we move away from the sample mean. Figure 11 reports the percentage points increase induced by a 10pp change at different hypothetical levels of the share of essentials using the full distribution of posterior predictive values. The shape of the distribution varies according to our estimation of the precision parameter ϕ. The kurtosis of the distributions suggests that as we move towards higher shares the prediction is progressively more uncertain, but the slight bimodality corrects itself in the same direction. The average marginal effect of the same 10pp increase of the hypothetical average share of essentials of 30% is 3.9pp. On the other extreme, a share of essentials of 70% shows an effect of 5.1pp. At 40%, 50%, and 60%, I find an effect of 4.3pp, 4.7pp, 4.9pp, respectively. Although uncertainty is too high to credibly separate the effects across different levels of the predictor, we can tell the extremes apart. Nonetheless, the differences are not large enough to suggest a severe cut-off point after which essentials lose completely their purchase on labor supply decisions. Although relevant, differences in the budget composition are not enough to support the existence of a cleavage in the work preferences of the poor and the rich, as distinguished by the pressure that essentials put on their budget autonomy.

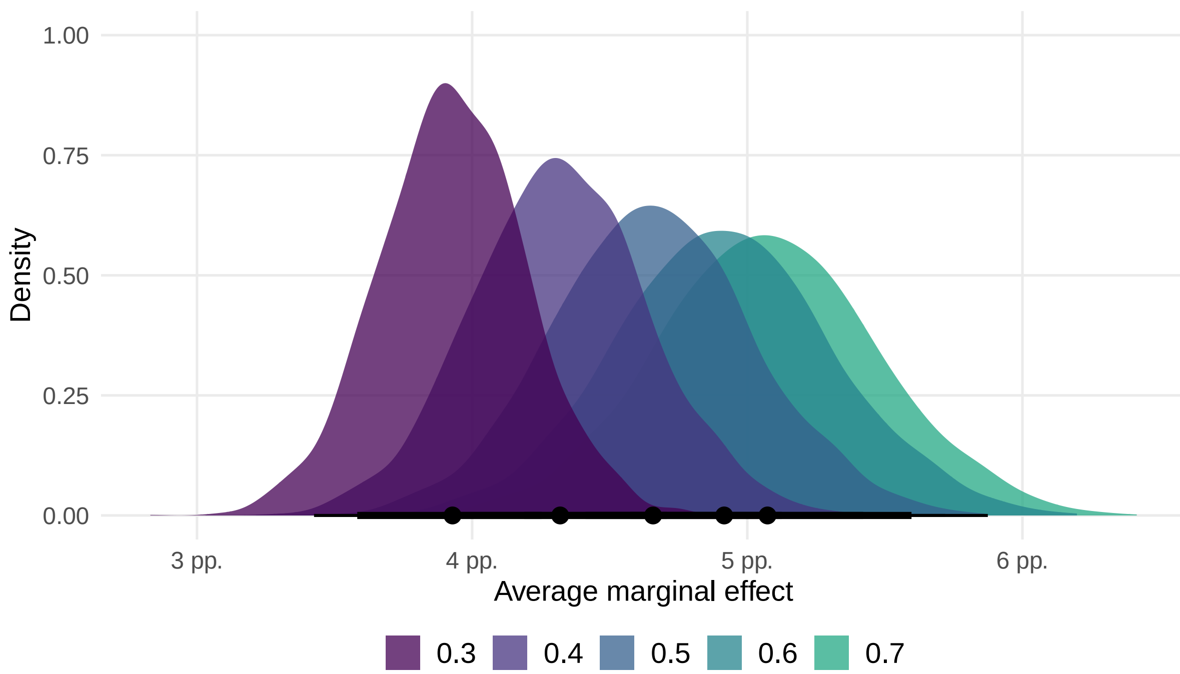

Figure 11: Average marginal effect of a 10pp increase in the share of essentials on the activity ratio of households. *Note*: 80% and 95% credible intervals shown in black. *Source*: Author's calculations based on ES-HBS data.

5 Discussion

This study has provided evidence showing that the burden of essentials on household budgets remained relatively stable between 1998 and 2022 in Spain, despite significant economic fluctuations and overall income growth during this period. This stability is observed across different bundle compositions and is primarily driven by the prices of food, utilities, and rent outpacing general inflation over the long term. As shown in Figure 9, this effectively negates some of the gains from real income growth. The stability of the share of essentials challenges conventional expectations about the effects of economic growth on household consumption patterns. According to Engel's Law and its time-series implications, we would expect the proportion of income spent on necessities to decline as real incomes rise (Chai and Moneta, 2010; Kaus, 2013). However, our results suggest that this relationship may not hold as strongly as previously thought. As shown in Figures 7 and 10, while the share of essentials at current prices displays a stationary trajectory, the share at constant prices trends downwards consistently. This indicates that households are reducing proportionally the quantity of food or energy they consume, as proxied by their deflated spending value, but their budget effort remains the same. The fact that households across different income levels, and *across time*, consistently allocate a similar proportion of their budget to essentials suggests that many families may find their budget space significantly constrained to save, accumulate wealth, smooth consumption, or choose between leisure and consumption (Shaikh, 2016; Işıkara, 2021; Wagenknecht, 2013). Ultimately, this challenges the notion of economic progress as a monotonic process that uniformly improves living standards across the board (Macekura, 2020; Vollrath, 2019). The results presented in the paper suggest that understanding the evolution of the share of essentials can help fill in the missing link between structural change and living standards.

As a series of studies have recently highlighted, inflation inequality is a persistent feature of advanced economies that tends to hurt poor households the most (Muellbauer, 1974b; Jaravel, 2021; Argente and Lee, 2020; Kaplan and Schulhofer-Wohl, 2017; Cage et al., 2018; Jaravel, 2019; van Kints and Breunig, 2020; Gürer and Weichenrieder, 2018, Basso et al. (2022); Bank of Spain, 2022). What our conclusions add to this literature is the characterization of inflation heterogeneity in the long run as an effect of the particular trajectory of structural change in advanced economies (Syrquin, 1988; Timmer et al., 2015; Krüger, 2008; Byrne et al., 2018; Inklaar and Timmer, 2014; Schettkat and Yocarini, 2006). It is well-known that computer prices have fallen dramatically, whereas inflation in education, healthcare, and personal services have systematically outpaced the CPI (Baumol et al., 2012; Raa and Schettkat, 2001; Parrinello, 2004; Palazuelos and Fernandez, 2009; Maroto-Sánchez and Cuadrado-Roura, 2009). Whereas some authors have pointed to the missing quality adjustment (Nordhaus, 1998; Boskin et al., 1996; Gordon, 1990), or argued that growth rates in the US and other advanced economies might have been overestimated by treating sectors like finance, healthcare, and personal and business services as final instead of intermediate output (Basu and Foley, 2013; Tercioglu, 2021; Assa, 2016), others have contended that the relative cheapening of many goods should generate opposite income effects that would compensate for healthcare or education growing more expensive (Baumol et al., 2012, 1985; Nordhaus, 2006). It also remains a possibility that current product innovations fall short of the revolutionary changes to the standard of living that electrification, running water, or the automobile brought forth in the past (Gordon, 2000, 2016). One way or another, it is clear that growth in real incomes does not represent as closely the improvement in living standards as its use as the indicator of economic progress would suggest (Macekura, 2020; Stiglitz et al., 2010). Otherwise, the time-series implication of Engel's Law would have driven the share of essentials down, consequently freeing the ability of households to choose. Therefore, without considering structural change, the analysis of living standards will remain blind to some of the consequences of the "stickiness" of the share of essentials.

To examine the most relevant implication of this macro pattern, the paper has introduced the analysis of the weight of essentials on labor supply. In the movement from "stochastic micro to macro", classical theory recognizes the relevance of the minimum real wage as the lower limit to the fluctuation of the real wage rate (Shaikh, 2016, 646). Whereas increasing evidence has emerged on the role of regulating capitals and real competition in constraining wage inequality across industries (Mokre and Rehm, 2020; Botwinick, 1993; Shaikh, 2016), this paper has tried to examine living standards as a collective constraint that underpins the lower limit to the (reproductive) wage rate inspired by the classical notion of a "socially determined" subsistence wage. The stationarity of the nominal share of essentials speaks of structural forces impinging upon workers' ability to bargain for higher real wages and or leisure time thanks to reduced dependence on the market to meet basic reproduction needs. Where mainstream economic theory understands that the supply of labor depends on a trade-off between consumption and leisure, classical theory introduces a crucial difference between those consumption items that "the custom of the country renders it indecent for creditable people, even of the lowest order, to be without" (Smith, 1976, V, ch.II) and those that households can give up in exchange for leisure and decide to distribute between consumption and savings. A prime example of this difference is studies that approach the secular decline of work hours as a partial consequence of the cheapening of recreation goods (Kopytov et al., 2023). Although essentials do not suffice to explain why households prioritize consumption above a minimum before deciding to save or work fewer hours, it underscores two relevant issues. First, the endogenous relationship between unemployment and wages needs to consider the minimum nominal wage rate to explain the movements of workers across industries and occupations. Second, the stability of the share indicates a debilitation of the growth-to-living-standards pipeline with possible feedback effects on labor discipline, social cohesion, and economic discontent. At the core of both issues is the understanding of micro patterns as collective authors and individual actors of systemic forces, and not individual choices, be they rational, irrational or whimsical (Shaikh, 2016, ch. 3). I find that this perspective is closer in spirit to classical political economy in its seeking to explain aggregate patterns or statistical equilibria via the "impersonal domination" of systemic constraints instead of direct political coercion (Postone, 1993; Rubin, 2016; Foley, 1986). All in all, the study of the relationship between labor supply and essentials is partial and limited, and it requires further examination.

Finally, I find that the persistence of a given budget effort to meet basic needs has implications for the study of poverty lines. The separation between poverty and inequality studies owes much to the difficulty in identifying a level of income that can map a bundle of goods and services considered essential for any individual or household (Ravallion, 1998). The lack of correspondence between deprivation in basic needs or capabilities and income or consumption levels is likely behind the dominance of multidimensional measurements of poverty (Alkire and Foster, 2011) and the frustration with aggregate indicators of living standards and relative poverty lines (Krishna Kumar et al., 2020; Milanovic, 2013; Reddy and Pogge, 2010; Shaikh and Ragab, 2007; Sen et al., 1987). Recent work challenging international (absolute) poverty lines (Sullivan et al., 2024; Moatsos, 2016; Allen, 2013; Reddy and Pogge, 2010), building on needs-based approaches to deprivation indicators (Rao and Min, 2018; Allen, 2017), address, precisely, the complexity of defining universal indicators of absolute deprivation that can apply to multiple income levels. Moreover, focusing on necessities provide insights into aspects of living standards that cannot be conveyed universally by money (Sullivan et al., 2024; Moatsos, 2016, 2021). By examining the relationship between real income and the share of essentials, the paper has sought to vindicate the potential of this relationship to contribute to developing overall poverty indicators that combine the absolute and relative aspects of poverty (Decerf, 2022; Atkinson and Bourguignon, 2001; Ravallion and Chen, 2011; Ravallion, 2016). Far from a niche implication, this observation can help explaining the "crisis of the middle class" and growing economic discontent in advanced economies (Milanović, 2019; OECD, 2019). Moreover, new research about how the pressure from essentials can affect the experience of consumer and worker autonomy may shed some light on the strong divergence between the aggregate state of the economy and individual perceptions, particularly since the COVID-19 pandemic.

6 Conclusions

Are living standards improving? We can confidently say that advanced economies have experienced at least two centuries of real income per capita growth (Gordon, 2016; Ravallion, 2016). In the last decades, and despite relatively low growth rates and increasing inequality, real disposable incomes have continued to increase for most of the population (Ribarsky et al., 2016). But discontent with economic progress is growing amid a cost-of-living crisis in rich countries. The premise of the paper was that inequality cannot explain persistent economic exclusion and only partially account for economic discontent beyond cultural or psychological motivations (Milanović, 2016; Moyn, 2018). Looking at the evidence presented in this paper, we find living standards stagnation in the data once we introduce a difference between essentials and non-essentials in household priorities and labor supply choices. This paper has proposed to investigate the claim that living standards are stagnating or even worsening in the long run for a non-trivial percentage of the population in advanced economies (OECD, 2019), which was approached using a relatively long series of Spanish household consumption expenditure data. Put differently, consumer choices for most people are uncorrelated with the level of real per capita income, which challenges the prevailing notion of economic progress as a monotonic process, as well as the assumption of non-separability of preferences for rational inter-temporal optimization in standard macroeconomic models (Macekura, 2020; Vollrath, 2019; Wagenknecht, 2013). Most importantly for the structural change and political economy literature, the results suggest that living standards have an endogenous component that precludes any sharp distinction between matters of poverty and distribution, as well as the identification of real income gains and economic independence. I find this connection crucial to examine the relationship between living standards and the classical theory of wages and unemployment (Shaikh, 2016), which I seek to continue in future research.

I identify three main limitations of this study, which present us with related research opportunities. Firstly, income information is known to be less reliable than expenditure data in the Household Budget Survey (HBS), which at the European level has driven efforts to produce more robust datasets on the joint distribution of income and expenditure using statistical matching techniques applied to the Survey on Income and Living Conditions (SILC) (Coli et al., 2022; European Commission. Statistical Office of the European Union., 2017). Reproducing the results using a synthetic HBS-SILC dataset may improve precision on the comparison of income levels using different price indexes, as well as offering additional analytical insights into demographic and income groupings. Secondly, the Spanish case is singular among advanced economies in at least two respects: it took the country more than a decade to approximate the nominal income levels of the 2007 peak, and it has a relatively high cost of living and income inequality within the European context. While offering a detailed long-term analysis, the focus on a single, medium-sized European country may limit the external validity of our findings. Generalizing the results to other OECD economies should be a priority to validate these results and to investigate the "crisis of the middle class life style" (OECD, 2019; Ribarsky et al., 2016). Finally, the empirical strategy has relied on a computationally intensive choice of estimator that required intervention on the dimensionality of the dataset, as well as pinning the group variance through a distributional extension of the Bayesian regression model. These choices could be more thoroughly tested using traditional estimators, and additional specifications, by drawing upon additional populations(Chai and Moneta, 2008; Kaus, 2013; Anker, 2011a) as a means to improve the robustness of the results. Further investigation into the micro-level dynamics of household decision-making could provide a deeper understanding of how families navigate the trade-offs between essential and discretionary spending in the face of changing relative prices.

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Appendix A: Weak statistical identifiability

It has been shown in the literature that the Bayesian implementation of complex (multilevel) models is subject to *statistical identifiability* issues. According to Gelman and Hill (2007, p. 68), weak identifiability is a statistical property of models in which some parameters "cannot be estimated uniquely." In principle, if the "posterior distribution is proper… then all of the parameters are identified" (McElreath, 2020, p. 169). The problem is that a reasonable or accurate interpretation of the posterior may not be possible. It is caused by the invariance of the posterior probability with changes in the parameters, such that variation in two different parameters may lead to the same likelihood. The most common instance is a given degree of collinearity among predictors (Bafumi et al., 2005). This causes the algorithm problems mapping the posterior density inside flat probability areas. Weak identifiability is, thus, not an inherent feature of the theoretical model but of the computation method. It leads to poor mixing and convergence of the sampling algorithm even in well-specified and data-rich estimations (Ogle and Barber, 2020). Moreover, it typically shows up as highly correlated chains and low effective sample sizes (ESS) that prevent us from obtaining trustworthy posterior samples.

This is the case in with the model described in equations (5) to (13), where the population-level intercepts α_0, α_0^{ϕ} are autocorrelated among themselves and with their respective group-level intercepts $\alpha_{j[i]}$, $\alpha_{j[i]}^{\phi}$. The autocorrelation of the chains decreases slowly with the number of iterations, and in some cases, it may never converge. To prevent this problem from affecting our samples, I implement the following three solutions in the interest of computational efficiency.

Firstly, one of the most prevalent solutions is to set the varying effects to a (hard or soft) sum-to-zero constraint, which consists of treating the $J-1$ varying effects as stochastic (14) and to obtain the remaining as the residual spread from zero (15). This is reported to result "in notable improvements in mixing and convergence of the MCMC chains" (Ogle and Barber, 2020, p. 12), especially with large group sizes. The case of a soft sum-to-zero constraint simply applies (14) for $j = 1, 2, ..., J$. In the present case, the hard and soft constraints led to a substantial reduction in chain autocorrelation. For computational reasons, the soft sum-to-zero constraint is the one implemented.

$$\alpha_j \sim \textbf{Normal}(0, \sigma_\alpha^2) \quad \text{for} \quad j = 1, 2, ..., J-1 \tag{14}$$

$$\alpha_J = -\sum_{j=1}^{J=1} \alpha_j \tag{15}$$

Secondly, I choose to implement the *post-sweeping* of the varying coefficients (Ogle and Barber, 2020, p. 12) as shown in (16) and (17), it consists of keeping the parameterization of the weakly identified quantities α_j to find the identifiable ones α_j^* by, first, subtracting ("sweeping out") the average $\bar{\alpha}$ population-level coefficient from the original varying effects α_j to, then, adding ("sweeping in") the weakly identifiable parameters to obtain the target quantities. Since only the intercepts suffer from weak identifiability, I apply this correction only to α_0, α_0^{ϕ}, $\alpha_{j[i]}$, $\alpha_{j[i]}^{\phi}$.

$$\alpha_j^* = \alpha_j - \bar{\alpha} \quad \text{for} \quad j = 1, 2, ..., J, \quad \text{where} \quad \bar{\alpha} = \frac{1}{J}\sum_{j=1}^{J} \alpha_j \tag{16}$$

$$\alpha_0^* = \alpha_0 + \bar{\alpha} \tag{17}$$

Finally, following the Bayesian consensus about the importance of informative or weakly informative priors to exploit previous knowledge and increase computational efficiency, it is possible to achieve pseudo-identifiability in most cases by centering the prior distribution on the expected value of the parameter or by containing the parameter space to a sufficiently small range without excluding the true posterior region (Gelman et al., 2017). Given the extensive data available, I use this solution to achieve substantial computational gains. Precisely because of this, the posterior is not very sensitive to the prior distribution, and I center the overall intercepts on the values obtained via automatic variational inference (Kucukelbir et al., 2015; Yao et al., 2018) for the whole sample and after running the model specified above on a random sample totaling one-fifth of the dataset. I further reduce the variability of the varying effects to the posterior uncertainty interval plus a margin.