Extreme Poverty in Wealthy Nations: Evidence from France*

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Abstract

We offer new empirical facts and insights into the determinants, dynamics, and consequences of extreme poverty in an advanced market economy, based on a novel administrative data set from France's largest food assistance charity that is unique in its comprehensive coverage of low-income households – in particular of homeless individuals. We quantify the impact of local macroeconomic conditions (such as unemployment rates, food and rent inflation, firm dynamism, social housing policies) and individual characteristics (such as demographic, financial, and duration variables) on entry into, and exit from, food insecurity and homelessness. We furthermore estimate non-linear marginal propensities to consume and price elasticities of consumption for housing (both on the extensive and intensive margins), non-housing, and reliance on the charity for food support. We document several novel facts. First, extreme poverty is largely a transient phenomenon, but a large fraction of the French population is at risk of falling into food and housing insecurity. Second, inflows into extreme poverty are much more sensitive to economic conditions than outflows, which depend only on individual characteristics and are strongly duration-dependent. Third, we find evidence that housing is a luxury good, with marginal propensities to consume housing equal to zero (respectively, strictly positive) below (resp., above) a threshold. Fourth, the high inflation period starting in 2022 plays a central role in accounting for rising rates of extreme poverty in the last four years.

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"Progress is more plausibly judged by the reduction of deprivation than by the further enrichment of the opulent. We cannot really have an adequate understanding of the future without some view about how well the lives of the poor can be expected to go."

Amartya Sen

1 Introduction

While we have by now detailed knowledge of the dynamics of income and wealth at the top of the distribution, thanks to the highly influential research agenda initiated by Piketty (2003) and Piketty and Saez (2003), much less is known about the other end of the distribution: the poorest households. What are the key drivers of deep poverty and its dynamics – what roles are played by family background and individual characteristics such as human capital, health, household composition, or idiosyncratic shocks, on the one hand, versus local economic conditions such as employment opportunities (or lack thereof), inflation, or the generosity of redistributive policies, on the other hand? These questions are particularly timely as recent evidence documents a rapid rise in extreme poverty in rich countries.

Data limitations, however, represent a major challenge for answering them comprehensively. Existing survey panels like the PSID and SIPP for the US or HFCS and EU-SILC for European countries struggle to capture the poorest households, particularly the homeless individuals who may be without a home or a phone at which they can be reached. Administrative tax data also paint an incomplete picture because they exclude undocumented immigrants or any other individual who does not have a tax identifier. Charity data can reach a broader population, but they may lack representativeness, e.g. because of an explicit religious affiliation or presence in a single city, and often have sample sizes that are too small to study heterogeneity across individuals or locations on a large scale. Empirical studies, especially of the homeless, thus tend to be much more limited in scope than studies of top income earners.

This paper attempts to fill this gap and offer new empirical facts and insights on the demography, geography, and dynamics of extreme poverty in an advanced market economy. We exploit a newly available semi-annual panel data set from France's largest food assistance charity that is unique in its coverage of low-income households. By our estimates and comparison with other data sources, our sample includes an extremely large share of the overall homeless population in the country, as well as many households in slightly less precarious situations, capturing approximately 1.5% to 2% of the French population and following them over space and time. Because the charity is present and active across the entire country, we are able to match households to the local economic conditions they experience, and examine

the role of person-specific and location-specific determinants of food and housing insecurity, as well as the efficacy of policies aimed at alleviating poverty. In addition, we observe each household's finances and are thus able to construct the budget constraint of the poor: labor income, transfers, pensions, several categories of expenses, and debt repayment.

Our data set has not been previously exploited by economists; thus, the first part of the paper consists of highlighting a number of descriptive statistics about the charity recipients. Because, for our purposes, documented and undocumented individuals are very different populations, in particular regarding their access (or lack thereof) to government-provided welfare benefits, we study these two groups separately.[1] For the subsample of French residents (citizens or immigrants having access to transfers), our first main finding is that *food insecurity (as defined by being present in our sample) and housing insecurity (i.e., homelessness) are both transient phenomena, but they affect a large share of the French population.* Specifically, the probability that an individual exits the sample within a year, conditional on being a recipient of the charity in the current period, is equal to 50%. Analogously, the probability of exiting homelessness a year from today is equal to 57%. This means that the average duration of a spell of food or housing insecurity is relatively short: $\sim$18 and 14 months, respectively.[2] However, there are more than 5.3 million unique identifiers between 2018 and 2025 in our sample, a figure comparable to about 8% of the overall French population (66.5 million inhabitants). Therefore, a very large number of individuals have had to apply for temporary food assistance and have been at risk of falling into extreme poverty in the past 7 years. Our descriptive statistics also reveal that the poor are overwhelmingly younger than the overall French population, they are much more likely to live in city centers (as opposed to suburbs and rural areas), and they tend to live in slightly poorer places.

The second part of our analysis goes beyond these raw descriptive statistics and studies more rigorously the determinants of entry into, and exit from, food and housing insecurity, along with the consumption patterns that such situations entail. Because the charity is present everywhere in the country, we can exploit spatial variations in economic conditions, such as the unemployment rate, average income, food and rent inflation, measures of firm dynamism and industry composition, availability of subsidized social housing units, homeless shelter capacity, and weather conditions, to estimate their impact on these outcomes.

[1] We are not legally allowed to reveal their respective shares in the overall data set. The statistics we provide always mention whether they are based on the whole sample or on one of the two sub-groups, but they do not allow the reader to recover the number of individuals in each subsample.

[2] While these durations may seem short at face value, spending a year in homelessness is, arguably, a very long time.

We also observe a number of individual demographic and financial characteristics of the recipients: age, marital situation, number and age of children, citizenship, usual language spoken at home, education, disability, housing status (private tenant, social housing tenant, homeowner, homeless and broader housing instability), labor market status (student, employed with type of labor contract, unemployed, out of the labor force, retired), earnings, all sources of welfare benefits, housing expenses (rent, utilities, taxes), debt repayment, and number of visits at the charity. We regress our outcome variables (probability of entering the sample or homelessness, probability of exiting, housing status, and housing expenditures conditional on housing status) on the local economic variables and individual characteristics of the household, along with season-location (e.g., "Paris in the winter") and season-year (e.g., "summer 2023") fixed effects. (We run the entry regressions at the local, rather than individual, level as we do not observe individuals before they enter the sample, nor the joint distribution of individual characteristics in the overall population of each location.) Thus, our estimates exploit the fact that economic conditions evolve over time by different amounts in different locations, while the national-level trends (e.g., Covid-related policies or aggregate inflation rates) are captured by the time fixed effect.

A potential concern is the endogenous selection of individuals into our sample. For instance, it is possible that those who are more likely to apply for food assistance at this charity are also more (or less) likely to get back on their feet and exit the sample, or spend systematically different shares of their budget on housing. To correct for this selection issue, our exit and consumption regressions control for the probability of entering the sample in the location and time period at which a given recipient first appeared. That is, we test whether places and times where entry is more likely also have systematically different exit flows or consumption patterns. Formally, our main identification assumption is that there exist instrumental variables that significantly affect entry into the sample, but only affect exits or consumption behavior through their effect on entry. Such variables include the number of drop-in centers of the charity in a given location and, for the subsample of homeless individuals, the levels of private and social housing rents.

This empirical analysis yields the second main finding of our paper: *Economic shocks and public policies have large and significant effects on inflows into food and housing insecurity, but they hardly impact the corresponding exit rates, which are only driven by individual characteristics.* In other words, recessions induce households to fall into extreme poverty at much faster rates than the subsequent recovery helps pulling them out. Specifically, we find that the main economic determinants of inflows into food insecurity and homelessness in a given

location are, on the one hand (with a positive sign), unemployment and rent inflation, and on the other hand (with a negative sign), average income, stock of social housing units, stock of firms (especially in certain industries). Quantitatively, we find roughly unit elasticities for several of these explanatory variables: a 10% increase in the unemployment rate leads to a 10.6% increase in homelessness and a 8.9% increase in food insecurity; a 10% increase in private rents leads to a 9.9% increase in homelessness; and a 10% increase in the stock of social housing units per capita reduces homelessness by 9.3%. A larger number of firms per capita has an even larger impact, with -3.37 and -0.67 elasticities on homelessness and food insecurity, respectively. We also find significant interaction effects: food and rent inflation have a larger predictive impact on homelessness in places where the unemployment rate is high. By contrast, none of these variables have an economically or statistically significant impact on exit rates out of food or housing insecurity. Instead, the key determinants of outflows are individual characteristics, with an especially strong duration dependence. In particular, reducing income from more than 800€ per consumption unit per month to less than 200€, or spending 3 years in the sample or into homelessness, both raise the exit rates by about 15 percentage points from a baseline of about 50% per year. These findings suggests that public policy affecting local labor and housing markets is able to help prevent people from falling behind, but helping them escape poverty requires early, individual-specific interventions.

The third main finding of our paper concerns the housing consumption patterns and their responses to household income and prices, which are key moments that macroeconomic models aiming to capture the bottom of the distribution should replicate. We show that *housing appears to be a luxury good, with marginal propensities to consume (conditional on housing status) close to zero up to a threshold, beyond which the housing MPC starts rising.* Specifically, we use our consumption regressions to estimate the non-linear impact of income on housing consumption, both on the extensive margin (private tenancy, social tenancy, homelessness, homeownership) and on the intensive margin (housing expenses) keeping all other covariates fixed at their average value. On the extensive margin, there is a clear (and unsurprising) declining relationship between the probability of being homeless and income, mirrored by an increasing relationship for private tenancy; and the probability of social housing tenancy is hump-shaped in income. Thus, the housing share of consumption rises with income. However, the intensive-margin relationship between housing expenditures and income is surprising. For both private and social housing tenants, the marginal propensity to consume remains equal to 0 up to a threshold of about 600€. It is only mildly positive for homeless individuals, whose housing expenses consist of occasional nights at hotels or

shelters, up to roughly the same income level. Above this threshold, housing expenses start rising significantly in all housing categories. These non-linear Engel curves imply that conditional on a housing status, every marginal euro of income up to a subsistence threshold is spent exclusively on other goods – food, clothing, transportation, etc. Our paper also estimates own- and cross-price elasticities of housing, non-housing, and within-charity consumption, disaggregated by income.

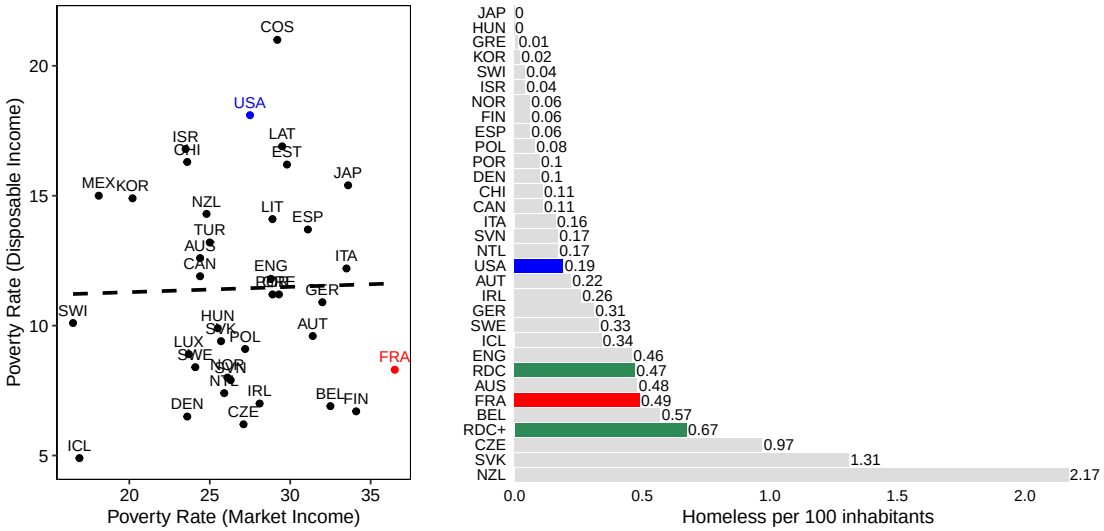
France in the OECD Context. Before moving on to the core of our analysis, we find it useful to place poverty and homelessness in France in the OECD context in Figure 1.[3] The left panel shows the poverty rate in each country, defined as 50% of either median market income (horizontal axis) or median disposable income (vertical axis). According to these data, France has the largest poverty rate among all OECD countries before taxes and transfers: 36.5% of its inhabitants earn less than half of the national median income. After taxes and transfers, however, France has one of the lowest poverty rates (8.3%). Thus, it is one of the most redistributive welfare states. The U.S., by comparison, has an average poverty rate among OECD countries before taxes and transfers, but does relatively little redistribution: after transfers, it has the second largest poverty rate (18.1%).

The right panel reports the OECD estimates of homelessness across countries, as well as the amount of homeless individuals in our sample. The OECD estimates that 0.49% of the French population is homeless (red bar), while our sample itself leads to homelessness rates between 0.41% and 0.61% depending on the precise definition (green bars; we provide further details about this comparison in Section 2.3 below). For comparison, the U.S. estimate is given by the blue bar (0.19%). Note that different countries use different methodologies to measure homelessness rates; for instance, New Zealand (the longest bar in the graph) includes broader forms of precarious housing (e.g., couch surfing, etc.) in their definition, while their estimate for France focuses more restrictively on individuals sleeping in the street. We refer to the OECD website for a detailed discussion of the methodology used to construct these estimates in specific countries.

Literature review Understanding who are the households facing food and housing insecurity, and what factors drive their behavior and their propensity to fall into extreme poverty, has long been hampered by data limitations and measurement errors (Hopper et al., 2008; Meyer et al., 2025c,a). An important recent exception is the work of Meyer et al. (2024), who link 140,000 homeless individuals from the 2010 U.S. Census to tax and safety-net records,

[3]Sources: here and here. Country-specific notes on the construction of the estimates of homelessness are available here: here.

Figure 1. Left: Poverty rates in the OECD (2022). Right: Homelessness rates in the OECD (2022) and in the RDC sample.



Notes: Poverty rates in the left panel are defined as the share of the population below 50% of the country's median income (before taxes and transfers on the x-axis, after taxes and transfers on the y-axis). The red bar in the right panel gives the OECD estimate of (strict) homelessness in France. The green bar labeled "RDC" gives the homelessness rate in our sample, using a similar definition as the OECD. The green bar labeled "RDC+" gives the homelessness rate in our sample, using the broader definition that includes all forms of unstable housing.

providing rare large-scale administrative evidence that homelessness is tied to persistently low incomes long before and long after the homelessness episode, despite partial attachment to both the labor force and social programs. Complementing these findings, Abdul-Razzak et al. (2025) show that homeless families are not disengaged from the labor market by choice, but rather face logistical barriers such as childcare, housing, and transportation that prevent them from working. Beyond individual labor market outcomes, housing market conditions have also been shown to play a central role in generating and perpetuating poverty: Collinson et al. (2024) document the role of eviction dynamics in shaping homelessness risk, Christopher et al. (2025) study the role of shelter provision on mortality risk and re-entry into homelessness, while Costantini (2025) show that housing provision significantly reduces mortality among unhoused veterans. These studies cannot easily establish how long the homelessness spells typically last, since doing so requires longitudinal tracking of large populations over time, nor correlate these events with macroeconomic shocks, which would require substantial cross-sectional variation in these economic conditions. Allgood and Warren Jr (2003) make progress on the former front, finding that spells are generally short among a survey of roughly 4,200 individuals, with more than half lasting under three months. Our paper revisits and extends these findings at a much larger scale, following millions of individuals

over several years and across a large spectrum ranging from strictly defined homelessness to broader conditions of food insecurity, and exploiting rich geographical heterogeneity across an entire country to establish the impact of economic shocks on these outcomes.

Our empirical findings also speak directly to a growing body of structural work that models homelessness, macro business-cycle exposure, and housing market risk (O'Flaherty, 2012; Mansur et al., 2002; Mitman, 2016; Imrohoroglu and Zhao, 2022; Favilukis et al., 2023; Abramson, 2023; Abramson et al., 2024; Corbae et al., 2024). These models fundamentally require as key inputs micro-level evidence on household financial conditions and spending behavior, the persistence of deprivation spells, and how exit and return rates vary with individual characteristics such as disability status. Our paper provides precisely these moments, which are central for evaluating the effectiveness of welfare programs, food assistance, and housing provision (Prendergast, 2017; Cohen, 2024; Costantini, 2025).

Finally, our analysis connects to the literature on the measurement of poverty at the very bottom of the distribution. Han et al. (2022) and Meyer and Sullivan (2023) have shown that income-based poverty measures can be especially misleading among the poorest households. Our data and findings strongly reinforce this concern: homeless individuals may report similar monthly incomes as renters living in a more affordable location, yet have far worse living conditions. Such a discrepancy underscores the value of consumption-based and multidimensional approaches to measuring deprivation.

Outline. Section 2 introduces our data and provides basic summary statistics and institutional context. Section 3 describes our econometric specifications. Section 4 gives our main results on the impact of local economic shocks and individual characteristics on (i) entry into, and exit from food insecurity and homelessness; and (ii) housing and non-housing consumption and reliance on the charity for food support.

2 Data Sources

2.1 Main Data Set (RDC)

Our data comes from the largest food bank and soup kitchen in France, "*Les Restos du Cœur*" (or "Restaurants of the Heart", henceforth RDC). This charity was founded in 1985 and provides recipients with hot meals, packaged food, hygiene and baby products, as well

as emergency shelter, educational, cultural, legal, and administrative support.[4] The crucial feature of this charity, for our purposes, is that households are eligible to receive food assistance for the next semester if their resources are below a given threshold. This particular rationing criterion leads RDC to collect data biannually on a wide range of characteristics of the individuals who apply for support. Since 2018, they have digitized and anonymized these data (with partial digitalization in 2017). This forms our main dataset. We observe all applicants, including those who were rejected.

Eligibility Criterion. Individuals are surveyed by RDC volunteers on a semi-annual basis, with a "summer" wave starting in March and a "winter" wave starting in November. In practice, most people apply within the first two months of each wave, but a significant fraction of recipients join some time between the start dates of two consecutive waves. Eligible households get access to free food until the beginning of the next wave. The eligibility criterion is based on the household's "rest for living" (*"reste à vivre"*), defined as the difference between all income sources and the recorded (mainly housing) expenses, as explained below. For instance, to be eligible in the winter 2024 wave, the household's rest for living must be lower than a nationwide threshold of 498€ per month for a single individual and 633€ for a couple with no children; more generally, eligibility depends on the number of family members and the age of children. If a household's rest for living is only slightly above the threshold, a collective decision is made by the volunteers about whether to grant eligibility, giving rise to a kink rather than a sharp discontinuity in the number of recipients around the eligibility threshold.[5]

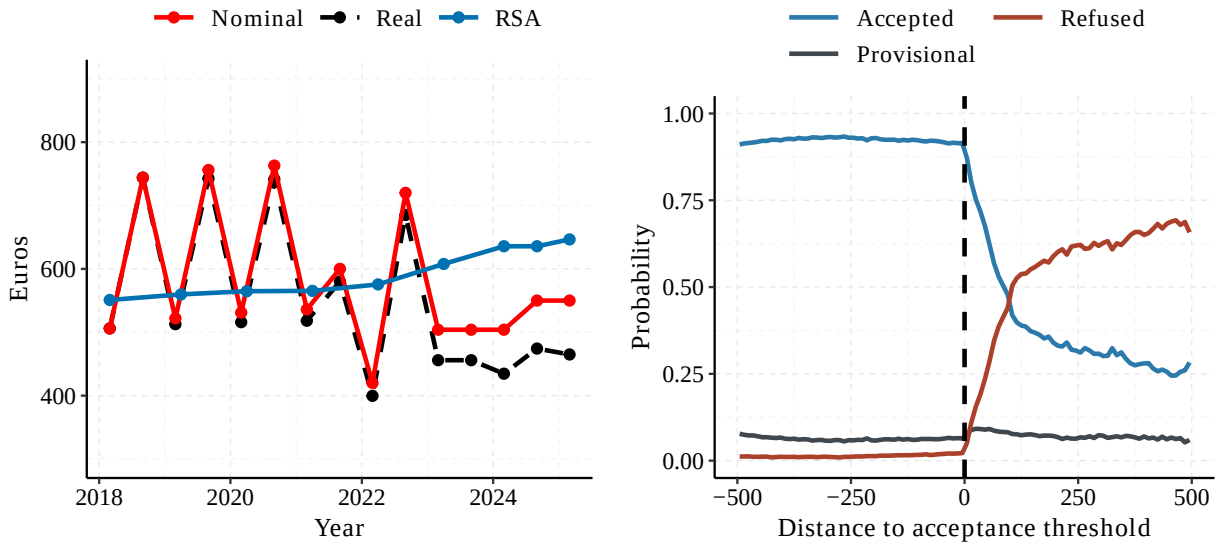
These eligibility rules are illustrated in Figure 2. The left panel shows the evolution of the monthly eligibility threshold over time for a single individual without children (red line, with inflation adjustment in black). Until 2023, the threshold was higher in the winter to reflect the higher heating costs. For reference, the blue line in the left panel reports the amount of RSA ("*revenu de solidarité active*"), i.e., monthly cash transfers to eligible individuals with no income – one of France's major redistributive policies that we describe in more detail in Section 2.5. The right panel of Figure 2 shows the probability of being accepted for food assistance as a function of the household resources net of their eligibility threshold.[6]

[4]Households get approximately one meal per person per day, generally consisting of 100 grams of protein product, 100 grams of vegetables, 100 grams of dessert, and either 1 yogurt or 30 grams of cheese or 20 grams of cream.

[5]Note that the committee members who make this decision are not in charge of collecting the data or distributing the food – thus limiting potential issues of favoritism by RDC volunteers.

[6]The right panel is constructed for the summer 2021 wave and for legal French residents only. The structural break at the eligibility threshold is under-estimated as we did not correct for the potential self-

Figure 2. Left panel: Eligibility threshold for single without children. Right panel: Acceptance probability (summer 2021 wave, French residents only).



Coverage of the RDC Data. Our data allows us to observe a large share of the very poor households in France, and, as we argue below, the near universe of the homeless. RDC is by far the largest food charity in France, and the only one that is completely free of charge for the recipients. It has an extremely fine spatial coverage, is well-known by virtually everyone in the country, and has an excellent reputation; in particular, it is not associated with any faith (nor lack thereof) or political party. All of these characteristics makes RDC a likely "first stop" for food assistance. For comparison, the second largest food aid charity, the *Secours Populaire*, currently serves fewer than 6,500 households in the city Paris each year, compared to more than 14,000 for RDC in 2024, and it has less than 1,300 local centers in the country, vs. more than 2,300 for RDC.[7]

Concretely, the left panel of Figure 3 plots the evolution of the number of RDC applicants over time (black line), and of the number of accepted recipients (blue line).[8] The sample includes roughly 450,000 households in 2024, or about 1 million individuals (for reference, mainland France including Corsica had 66.2 million inhabitants in 2024). The left panel of Figure 3 also reports the overall number of homeless individuals in our sample: about 300,000 under the strictest definition of homelessness (dark red line), and between 400,000 and 500,000 (i.e., 1 homeless individual per 150 inhabitants, or 0.61% of the French population on

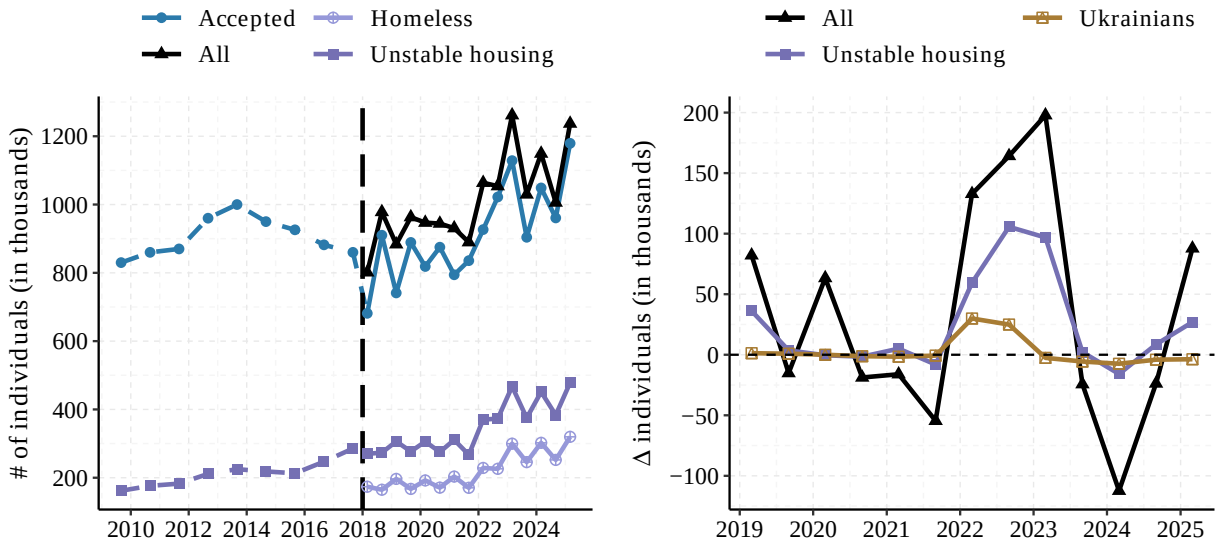
selection of applicants who choose not to apply if they presume that they will fall to the right of the eligibility threshold.

[7]Source here. Note that households may receive food assistance from both RDC and other charities.

[8]Recall that the data was only partially digitized before 2018.

average) under a broader definition that includes various forms of unstable housing situations described below (light red line). The historical annual reports of RDC allow us to measure the number of recipients and homeless individuals as far back as 2009. Overall, our data contains 5.37 million unique individuals (respectively, 1.94 million experiencing homelessness) across all waves between 2017 and 2025, i.e., about 8.1% (resp., 2.9%) of the French population. We interpret these latter numbers as the amount of individuals who were at risk of falling into food insecurity (resp., housing insecurity) within the last 8 years. Notice that the post-pandemic period has been marked by a very large – between 20 and 30 percent – increase in the number of both overall and homeless recipients.[9] While we show below that the high rates of inflation rates between 2021 and 2023 explain a large share of this increase, the right panel of Figure 3 measures the share that is due to the invasion of Ukraine by Russia and the subsequent immigration of Ukrainian refugees in France.

Figure 3. Left panel: Number of observations (accepted recipients and all applicants). Right panel: Impact of the invasion of Ukraine by Russia on the rise in homelessness.



Note: The left panel shows the total number of applicants (black), those accepted into the program (blue), those in unstable housing situations (red), and those experiencing homelessness (orange). Data before 2018 come from RdC *annual* (winter campaign) records; from 2018 onward, they are constructed by aggregating the micro-panel data. The right panel shows year-over-year variation within the same season; e.g., it reports the change in the number of homeless households between winter 2024 and winter 2023.

RDC has a very fine geographical coverage. The left panel of Figure 30 shows the spatial distribution of its local branches (*centres d'accueil*, henceforth referred to as "drop-in centers"): the black (respectively, red) dots give the location of those that already existed

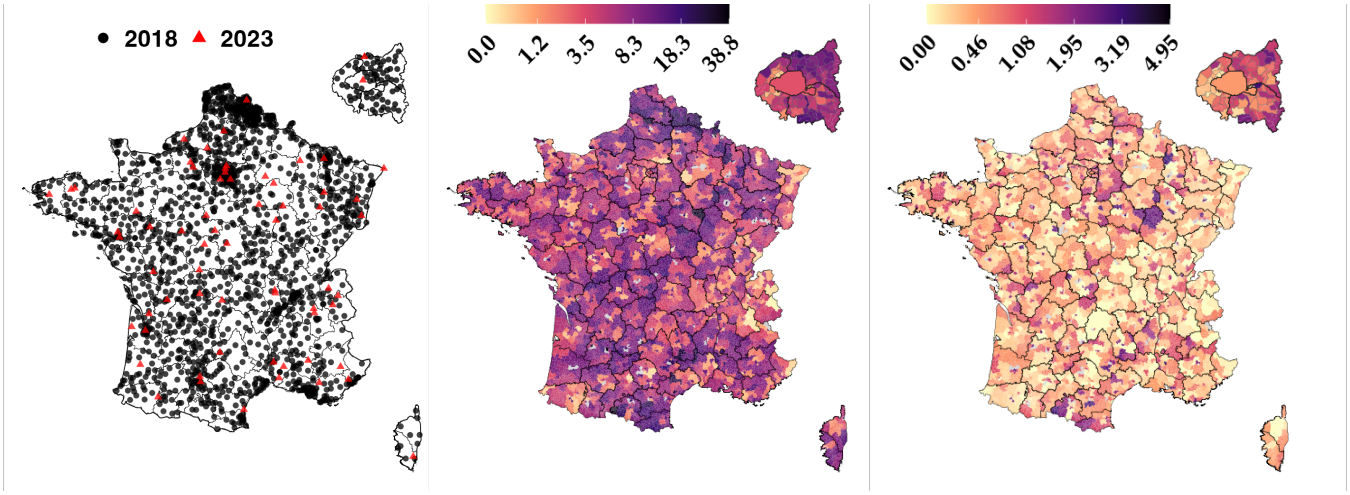
[9]RDC was able to raise the quantities of meals served without lowering eligibility criteria by tapping into their financial reserves and orchestrating a particularly successful fundraising campaign.

at the beginning of our data set (resp., those that opened between 2018 and 2023). As of 2025, there are 2,348 drop-in centers across mainland France. This represents more than 1 site per 30,000 inhabitants, or an average of 1 center per 90 square miles (or 230 km^2). This means that, if they were evenly distributed across space, everyone in the country would live within 7 miles (or 11 km) of an RDC center. About 45% of the drop-in centers are in urban areas, and 55% in rural areas.

The middle and right panels give the number of RDC recipients and homeless recipients in 2023, respectively, as a share of the population of the local *canton* (an administrative entity roughly equivalent to a commuting zone).[10] These maps show a significant amount of spatial variation that we will exploit later to explore the determinants of extreme poverty. There are high rates of poverty (defined as the number of RDC recipients) and/or homelessness in the suburbs of Paris, in the north along the Belgian border, in the south along the Mediterranean, and in the "empty diagonal" ("*diagonale du vide*") that covers the low population density areas from the north-east to the south-west of France.

Figure 4. Spatial coverage and intensity of RdC activity. French residents only.

(a) RDC drop-in centers (b) Recipients/1,000 households (c) Homeless/1,000 households



Note: Paris and its neighboring suburbs are expanded on the top right of each map.

Variables in the RDC Data. First, RDC gives each applicant and all of their household members both an individual and a household identifier. Importantly, applicants keep their individual identifier even when they re-enter the sample after exiting it, when they move to a

[10] There are 4,058 cantons and 96 départements in mainland France. Cantons (respectively, départements) are thus on average 53 (respectively, 2,220) square miles large, and have 20,700 households (respectively, 320,000) on average. The city of Paris (1.47 million households) is both a single canton and a département.

different location (they can only receive food from the location to which they applied in the latest wave), or when they form a new household after, e.g., getting divorced or leaving their parents' household. This feature allows us to track migration patterns, changes in household structure, and intergenerational linkages. Moreover, we observe when an individual first applied to RDC, even if this predated the first year of our sample. However, we do not observe individuals before they enter, nor after they exit, the sample – we do not know whether they exited because they found a job, and if so with what salary, or because they prefer seeking help from another charity, or because they moved out of the country or passed away.[11]

Second, we observe several socioeconomic characteristics. We know the birth date and gender of each member of a household; and for the household head, we observe their zip code, citizenship (French, non-French EU citizen, or Other), usual language spoken at home, highest educational degree, health insurance coverage, and disability status. We also observe the income and some expenses of each household member. Income consists of wages, pensions, all categories of government transfers (described in more detail in Section 2.5), alimony received, and "other regular income". Expenses consist of rent, mortgage, and other housing expenses (e.g., hotel rooms), housing and property taxes, utilities (water and energy), alimony paid, a dummy variable for indebtedness, and the amount of debt service if any. Furthermore, we know how often they collect food from RDC during the period, allowing us to construct a measure of their consumption within the charity by evaluating the price of the basket of goods that they receive. In addition, the data reports their labor market status: salaried worker on a short-term contract ("CDD"), long-term contract ("CDI"), or apprenticeship ("*alternant*"), self-employed (entrepreneur, farmer, artisan), unemployed, student, retired, out of the labor force (working from home, disabled, or without a legal right to work).

Third, applicants report their housing situation. They can be homeless or in other unstable situations, public (or "social") housing tenants ("*logement social*"), private housing tenants, or homeowners. Individuals in unstable housing categories are either homeless (living in the street, hospital, hotel room), without personal accommodation (living in a shelter, women's shelter, migrant shelter, halfway house and other collective housing), with precari-

[11]Regarding deaths, the association "*Les morts de la rue*" found that in 2023, a total of 702 homeless individuals passed away in mainland France, including 313 in the Paris metropolitan area (*Ile de France*). While an average of almost two deaths every day is tragic, this amounts to less than 0.25% of all the homeless individuals (with and without shelter access, but excluding broader unstable housing situations) in our sample. In the U.S., Meyer et al. (2025b) and Christopher et al. (2025) find that homelessness is associated with higher mortality. In the later, it is about 3.5 times that of the housed using large-scale administrative data.

ous accommodation (hosted by family or third party, subletting, in shared housing, threatened with eviction, in illegal housing), or with inadequate housing (caravan, mobil-home, tent, makeshift dwelling, squat). Throughout the paper, we refer to (strict) homelessness as the first of these categories, and to unstable housing, or broad homelessness, as their union. Social housing (mostly "*habitation à loyer modéré*" or "HLM") is one of the most important redistributive policies aimed at limiting the housing expenses of low- and moderate-income households. Social housing tenants benefit from subsidized rents. We estimate below that the ratio of social housing rents to private housing rents paid by tenants benefiting from housing subsidies, controlling for location and size, is on average equal to 75% in 2022-23.[12] In 2016, there were 4.8 million social housing units in France, or about 17% of all housing units and almost 50% of all rental housing units. About half of social housing tenants have income in the bottom 25% of the population.[13]

2.2 Additional Data Sets

We merge our main data set with a number of additional data sources.

Housing Rents and Availability. We first collected measures of rents and housing availability. The French administrative welfare benefits data (*Caisse d'Allocations Familiales*, or CAF) allows us to compute the rents paid by all individuals who receive any kind of transfers. We can therefore measure the average rents of private housing units at the local (canton) level. These housing units are by definition occupied by low-income tenants and are therefore the relevant housing market for households in our sample. In addition, we exploit a data set that contains the quantity and prices (overall and per square meter) of all private rental units available for rent at the zip code level, obtained from the systematic scraping of online listings.[14] This allows us to measure the rents of vacant units, which homeless individuals can potentially move to, as opposed to the rents of the currently occupied units reported in the CAF sample. Publicly available government data give us the distribution of rents of occupied social housing units at the local level.[15] We also observe, in each location, the stock of social housing units, as well as their vacancy rate. Finally, we collected adminis-

[12]INSEE (Institut National de la Statistique et des Etudes Economiques) estimated that in 2006, the ratio of social to private rents, controlling for location and various characteristics, was on average equal to 54% (source: click here). The difference with our estimate is that we compare the social housing rents to the private rents paid by low-income households, whom we think form a more natural comparison group.

[13]Source: click here.

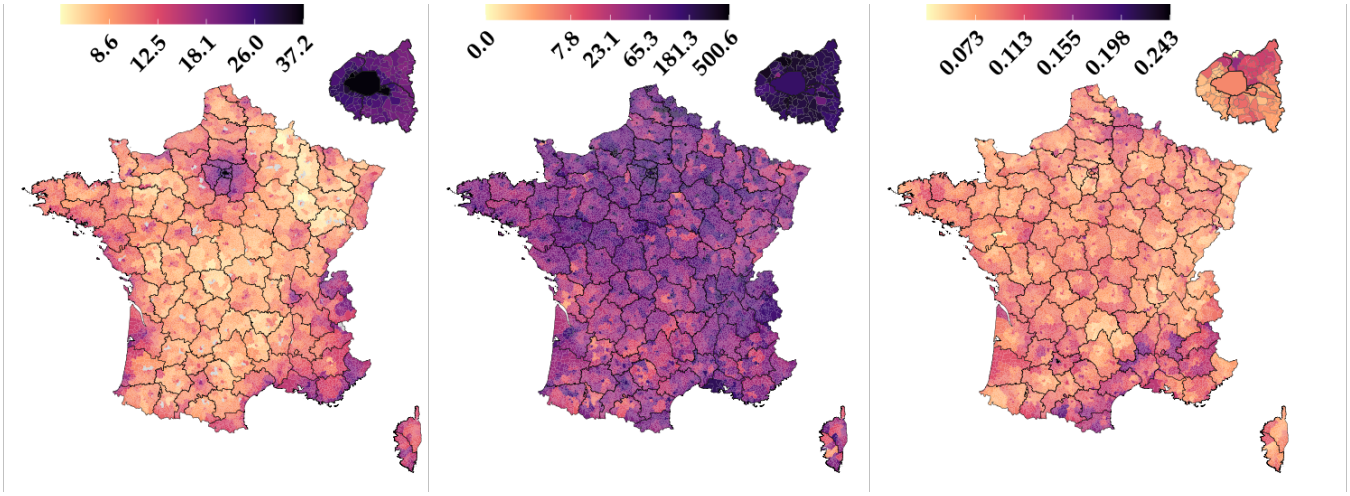
[14]We thank Guillaume Chapelle for sharing these data with us.

[15]Source: here.

trative data on the number and capacity of homeless shelters (*Centres d'Hébergement et de Réinsertion Sociale*, or CHRS).[16] The left and middle panels of Figure 5 depict the spatial variation in private rents and stock of social housing, respectively.

Figure 5. Selected local (canton-level) economic conditions.

(a) Private rent (b) Social housing/1,000 households (c) Unemployment rate



Note: Paris and its neighboring suburbs are expanded on the top right of each map.

Food Prices. Second, in order to explore the role of food inflation in driving poverty, we purchased bar code-level scanner data from . Similar to the Nielsen data set used by, e.g., Kaplan and Schulhofer-Wohl (2017), this data set contains the prices and quantities purchased by a panel of individuals, along with their demographic and income characteristics, in more than 300 stores (the 50 most common ones being almost exclusively supermarkets). Most of the bar codes correspond to either food items or, to a lesser extent, cleaning and personal hygiene products. After basic cleaning of the data, we observe the purchases of ≈ 7,500 to 15,000 individuals, and between ≈ 130,000 and 160,000 bar codes, per year. Aggregating at the *département* level, we have in 2023 – the year with the smallest number of individuals – an average of 80 individuals per département (min = 7, max = 369), and an average of about 10,000 bar codes per location (min ≈ 1,200, max ≈ 33,000). This data set allows us to compute local price indices and inflation rates as a volume-weighted average of prices of all bar codes in each year and département. The right panel of Figure 15 shows the spatial variation of the food inflation rate between 2016 and 2023.

Other Local Variables. Third, we merge our data with several other local covariates (all at the canton level): average income per capita, population size and density, unemployment

[16] Sources: here and here.

rate, inequality, gas prices, stock of firms, business creation (sole-proprietor or other firms), industry composition, temperature and rainfall, public amenities, election results (municipal elections took place in 2008, 2014, and 2020).[17] The right panel of Figure 5 show the spatial variation of the unemployment rate in 2023.

RDC Surveys. Finally, RDC runs additional quantitative and qualitative surveys on a small sample of about 1,500 recipients.[18] The latest survey asked several questions on mental and physical health – whether the recipient experiences disability, chronic disease, symptoms of depression, and how they would rate their physical health on a scale from 1 to 10. It also contains questions on housing quality (size, heating, humidity), leisure activities, child care and education, transportation, technology access, take up welfare benefits, access to help or support. For each of these items, the survey respondents also report whether they face financial, administrative, time, mobility, or psychological hurdles, and whether they expect their situation to improve in the future. We do not attempt to (imperfectly) merge these qualitative surveys with the main sample, but instead use it as a source of additional descriptive information that is useful for some of our findings.

2.3 Accuracy and Representativeness of RDC Data

In Appendix A, we evaluate the reporting accuracy of our observations. Applicants may have incentives to under-report income or over-report expenses in order to clear RDC's eligibility threshold. This issue is partly alleviated by the fact that they must, to the extent possible, provide verifiable evidence of their income and expenses whenever they apply to renew their enrollment. For instance, if they report earning a certain level of income that allows them to be eligible to some government transfers, they must show proof that they are indeed receiving these transfers. Such a verification is, however, more difficult for non-residents, e.g. undocumented immigrants who are not eligible to receive any transfers.

Appendix A also discusses the extent to which our data is a selected sample of the poor living in France, by comparing them to available survey data (HFCS and EU-SILC) and, for homeless individuals, to independent OECD estimates. Our first main finding is that survey data are severely mis-representing the bottom tail – just like for the top tail, these surveys seem to be plagued by under-sampling and mis-reporting issues. In addition, they

[17] Most of these local data are publicly available on the data.gouv.fr website. We also used Piketty and Cagé's local inequality data, OFGL for recent population data, INSEE for the stock of firms and new creations as well as amenities, French Ministry of the Interior for crime and delinquency.

[18] This subsample is not random, e.g., it overweights French-speaking individuals.

are typically unable to capture people currently experiencing homelessness, because they sample only private households living in an ordinary main residence. As a result, extreme poverty and housing exclusion are systematically under-represented in these data sets.

Our second main finding is that our data set captures an extremely large share of homeless individuals in France. To our knowledge, the most comprehensive and reliable outside estimate of the overall number of homeless individuals in France is that measured by the OECD.[19] They confronted multiple reliable sources to estimate that France counted 333,000 homeless individuals in 2022, representing 0.49% of the total population. Their definition of homelessness includes people sleeping in a place not intended for habitation or in an accommodation without rental contract (including refugee shelters), but ignores individuals living in other unstable conditions (e.g., hosted by third parties, etc.). Using a similar definition, our data in 2022 yields a rate of homelessness of 0.41% on average across the two waves of the survey, or about 84% of that estimated by the OECD.[20,21] Including precarious and inadequate housing conditions, which we also observe in our data, further raises this population share to 0.61%, i.e., 124% of the OECD count. These results are reported in the right panel of Figure 1, which also gives the homelessness rates of all other OECD countries. The main take-away is that our data appears to contain a very large share of the homeless individuals as estimated by the OECD, as well as an additional 40% "broadly homeless" individuals in unstable housing situations, who are also extremely difficult to capture in standard data sources.

To conclude, while it is difficult to establish with certainty that our sample is indeed representative of overall poverty in France, our view is that it is worth studying in and of itself as a snapshot of *food insecurity* (by definition, RDC recipients face severe deprivation to the point of requesting food assistance) and *housing insecurity* (since we observe flows into and out of homelessness or unstable housing more broadly). These outcomes account

[19] Source: click here.

[20] More precisely, there are 210,005 (resp., 335,790) individuals who report being either homeless or in shelters (resp., in other unstable situations) in the 2022 winter wave, and 228,647 (resp., 368,616) in the summer wave. Among the non-responses to the housing question, a fraction (around 25% for the French residents and 90% for the non-residents) of applicants also report having 0 housing expenses. We include these observations into homelessness, thus raising the total count by an additional 39,453 individuals in the winter, and 75,128 individuals in the summer.

[21] The similarity of our estimate and that of the OECD might hide composition effects. First, one of the sources used by the OECD (the INSEE homelessness survey, which dates back to 2012), focuses on cities with more than 20,000 inhabitants, with some information about cities with more than 5,000 inhabitants. Since we also observe homeless individuals in smaller towns, it is possible that we under-estimate the number of homeless in bigger cities by an equivalent amount. Second, the OECD defines homelessness as having been unhoused "the previous night". Our bi-annual survey might miss households facing such transitory shocks and capture more permanent situations.

for various observable or unobservable factors – such as the cost of living in the area where the recipient lives, the support network (or lack thereof) to which they may have access, etc. – which would be overlooked by restricting attention only to their income or financial resources.

2.4 Summary Statistics

This section summarizes some simple descriptive statistics about our sample. Because they are such different populations (e.g., regarding their access to government transfers), we separate the sample between French residents vs. non-residents.[22] We do not have an explicit variable indicating legal residency status, however. We thus consider that a recipient is a French resident if they are either (i) a French citizen; or (ii) an immigrant who receives any kind of government transfer other than the asylum allowance; or (iii) an immigrant who reports having applied to, but not yet received, government transfers. In general, non-French EU citizens must wait to reach 3 months of legal residency to be able to claim the RSA transfer, while non-EU citizens must wait 5 years. Thus, our analysis counts as non-residents the foreigners with legal status from an EU (resp., a non-EU) country but less than 3 months (resp., 5 years) of residency, as well as those who do not take up any of the transfers they would be eligible to.

French Residents. Table 1 presents basic summary statistics – averages across sample waves – for French residents only, both for the overall sample and for subsamples defined by specific housing statuses: private tenants (31% of the sample), social housing tenants (45% of the sample), and homeless or broader unstable housing situations (18% of the sample); the remainder are homeowners.

Starting with the demographic characteristics, resident RDC recipients are 46 years old on average (vs. 51 years old for the overall French population); 33% of them live in a couple (vs. 59% for the overall French population); they have one child on average, and slightly less than 20% of their children are younger than 3 years old. Compared to other recipients, social housing tenants are more likely to be single women (50% vs. 44% in the whole sample), older, with children, and French. By contrast, the subsample of homeless recipients is younger (40 years old on average, with a share of students that is twice as large as in the overall sample), much more likely to be single men (37% vs. 24% for the overall sample), less likely to be disabled (5% vs. 9% in the whole sample, and 6.6% for the overall French population), and

[22] We are not allowed to reveal the size of these two subsamples.

Table 1. Summary statistics for French residents: full sample and by housing status.

	RDC Resident Subsample								France[a]
	Full Sample		Private Rental		Social Housing		Unstable Housing		
Variable	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean
Demographics									
Age	45.95	(14.45)	45.46	(14.63)	47.87	(13.77)	40.42	(14.09)	54.7
Family consumption units	1.56	(0.634)	1.55	(0.629)	1.61	(0.640)	1.43	(0.594)	1.51
Couple	0.325	(0.468)	0.339	(0.473)	0.330	(0.470)	0.274	(0.446)	0.590
Single man	0.239	(0.426)	0.247	(0.431)	0.175	(0.380)	0.373	(0.484)	
Single woman	0.436	(0.496)	0.414	(0.493)	0.495	(0.500)	0.353	(0.478)	
# children	0.948	(1.29)	0.935	(1.28)	1.04	(1.32)	0.774	(1.19)	1.035
# children aged 0–3	0.172	0.438	0.166	0.428	0.170	0.434	0.200	0.470	
# children aged 4–12	0.543	0.918	0.541	0.911	0.604	0.950	0.425	0.827	
# children aged 13+	0.233	0.537	0.228	0.532	0.265	0.561	0.149	0.447	
Disabled	0.091	(0.288)	0.096	(0.294)	0.097	(0.296)	0.054	(0.226)	0.041
French nationality	0.628	(0.483)	0.674	(0.469)	0.640	(0.480)	0.526	(0.499)	0.912
Student	0.027	(0.161)	0.035	(0.185)	0.013	(0.115)	0.051	(0.221)	0.050
Retired / pre-retired	0.113	(0.316)	0.113	(0.316)	0.125	(0.331)	0.058	(0.233)	0.283
Finances (per CU)									
Work	0.108	(0.311)	0.123	(0.329)	0.102	(0.303)	0.072	(0.259)	0.530
Earnings	78.64	(210.26)	96.20	(235.52)	66.09	(189.59)	68.87	(186.99)	
Total income	667.67	(292.91)	730.27	(280.97)	712.30	(253.07)	463.44	(300.62)	2256.98
Transfers	459.30	(321.25)	488.65	(335.50)	510.47	(300.25)	330.37	(303.05)	188.74
Housing benefits	122.02	105.99	149.63	107.86	150.66	88.74	41.07	91.01	
Income w/o housing benefits	626.26	288.81	676.66	285.19	662.51	256.93	449.15	289.03	
Housing expenses	237.18	(293.25)	326.54	(276.36)	251.45	(349.34)	101.70	(150.07)	326.56
Expenses (incl. other regular)	309.54	(233.60)	400.93	(206.20)	338.59	(218.12)	132.65	(191.54)	
Total income minus housing expenses	430.49	(294.45)	403.77	(290.48)	460.85	(290.25)	362.74	(285.55)	1930.42
Resources left for consumption	358.13	(264.75)	329.34	(260.78)	373.71	(260.33)	330.79	(255.45)	
Consumption according to RDC	52.99	(37.28)	52.20	(36.22)	56.40	(37.36)	47.59	(39.14)	
In debt	0.155	(0.362)	0.155	(0.362)	0.181	(0.385)	0.088	(0.283)	0.438
Debt repayment (for indebted)	113.68	(320.92)	119.14	(277.45)	95.65	(346.51)	117.55	(271.19)	
Survival in sample									
Goes to the charity next year	0.507	(0.500)	0.511	(0.500)	0.556	(0.497)	0.431	(0.495)	
Local covariates (canton level)									
Annual income per capita (in k€)	15.21	(3.97)	14.87	(3.55)	15.28	(4.10)	15.97	(4.55)	17.13
Unemployment (broad) rate (%)	20.77	5.29	20.94	5.39	20.92	5.28	20.21	5.09	18.28
Private rent (€/sqm)	13.21	(5.48)	12.25	(5.03)	13.62	(5.50)	14.67	(6.06)	14.08
Private rent (CAF, €/sqm)	9.76	3.20	9.14	3.01	10.01	3.15	10.61	3.54	10.38
Social rent (€/sqm)	5.63	(0.822)	5.48	(0.813)	5.70	(0.788)	5.82	(0.882)	5.77
Private rentals per k hh	77.37	(54.62)	72.14	(51.08)	80.71	(56.13)	80.70	(55.11)	66.31
Social housing units per k hh	155.39	(94.58)	125.32	(88.38)	178.77	(93.62)	163.89	(90.96)	129.87
Shelter capacity per k hh	8.29	(8.61)	6.53	(7.90)	9.26	(8.71)	10.12	(9.17)	7.17
Price index	110.19	(9.52)	109.65	(9.42)	110.68	(9.60)	111.90	(9.72)	109.35
Firm stock (per k hh)	131.85	(45.03)	130.36	(41.38)	131.50	(46.85)	139.69	(48.43)	142.12
Urbanization									
City center	0.510	(0.500)	0.503	(0.500)	0.529	(0.499)	0.512	(0.500)	0.317
Suburb	0.299	(0.458)	0.235	(0.424)	0.337	(0.473)	0.337	(0.473)	0.379
Isolated city	0.112	(0.316)	0.141	(0.348)	0.092	(0.290)	0.094	(0.292)	0.090
Rural area	0.079	(0.270)	0.121	(0.326)	0.041	(0.198)	0.057	(0.233)	0.214
Share of observations	100%		30.65%		45.38%		18.44%		

[a] *Notes:* Overall France values are gathered from INSEE and EU-SILC for individual information (age, couple, etc.). Note that housing expenses are low because of the large share of homeowners (with low housing expenses) in France relative to the sample. For local covariates, we report the canton averages or postal code averages (for urbanization), weighted by population, between 2018 and 2023.

less likely to be French citizens (53% vs. 63% in the whole sample).

Turning to location characteristics, a majority of RDC recipients – regardless of housing

status – are located in city centers (51%), compared to only 32% of the overall French population. By contrast, only 8% of the recipients live in rural areas, vs. 21% for the French overall, despite the strong presence of RDC drop-in centers in these places. Thus, extreme poverty is a mostly urban phenomenon. Social housing tenants and homeless households are otherwise more likely to be located in suburbs, while private tenants are much more likely to live in isolated cities or rural areas, than the rest of the sample. Finally, RDC recipients (regardless of housing status) tend to live in slightly poorer and less economically active areas, with 15k€ taxable income per capita vs. 17k€ for France overall,[23,24] and 8% fewer firms per capita than in France as a whole. Using a broad definition of unemployment that includes marginally attached workers (part-time workers who are actively looking for a job), RDC recipients live in locations that have 21% unemployed, vs. 18% in the country as a whole.[25] The cantons in which RDC recipients are more likely to live also have lower rents (9.80€ per square meter vs. 10.40€ in France overall for units occupied by welfare benefit recipients, and 13.20€ vs. 14.80€ for new listings), but they have experienced slightly higher inflation between 2018 and 2023 (+10.2% vs. +9.4% for food prices).

Consider next the household-level financial variables, expressed per consumption unit (CU) in 2025 euros. Table 1 presents the unconditional values, which result from a combination of extensive and intensive margins; the corresponding income, transfers, and expenses conditional on receiving or paying them are given in Appendix C.4. Less than 11% of the French resident households in our sample have at least one household member who is em-

[23]Note that France has a GDP per capita that is significantly larger than this value: between 35,000 and 40,000€ during the time period covered by our sample. The definition of average income that we use in a location is the *revenu fiscal de reference*, which includes salaries, pensions, self-employment and rental income; see here.

[24]For comparison, the average annual income per household (instead of per capita) is 29,348 for France, and 27,240 in our full sample.

[25]The official unemployment rate in France is around 8%, computed using the International Labor Organization definition of unemployment and expressing it as a share of the labor force. There are two issues with this measure. First, we do not know the ILO-based number of unemployed individuals at the canton level; instead, we rely France's administrative data and *France Travail*'s official definition that includes unemployed workers in three categories: A (job seekers with no job and actively seeking employment), B (job seekers with a short-term reduced activity, defined as 78 hours or less in the month, and actively seeking employment), and C (as in B but for with a long-term reduced activity, defined as more than 78 hours in the month); see here. The second issue is that we do not know precisely the number of individuals in the labor force in each canton; we only observe the total number of individuals in the labor force in France, and the number of households in the labor force in each canton. We compute an unemployment rate at the local level by dividing the number of unemployed individuals (A+B+C) by 1.22 times the number of households in the labor force, where 1.22 is the national ratio between the number of individuals in the labor force (30,851 million in 2023) and the number of households in the labor force (25,371 million); see here. This constant in the denominator has no impact at all on our estimates, since it affects all cantons uniformly by construction.

ployed;[26] the resulting average earnings in the sample are 79€ per month, or about 480€ per CU conditional on being in a household with an employed member (see Figure 22). Their total income, however, is larger: 668€ on average, most of which consists of transfers (459€). Homeless recipients are less likely to be employed (7%) and have lower income on average (463€, in part but not only because they do not receive housing subsidies). For future reference, we construct a counterfactual measure of income ("income net of housing benefits") that excludes housing subsidies (APL) and adjusts the corresponding level of the RSA transfer – this variable, reported in Table 1, has the advantage of being exogenous to the choice of housing status of the household, which we treat later as an outcome variable in our empirical analysis.

Next, recipient households spend on average 310€ in housing expenses (rent, mortgage, taxes, other housing expenses, and utilities). About 15% of them are in debt, and their average monthly debt service is 114€. Homeless recipients are less likely to be in debt (8.5%); they also have lower expenses. The latter is mostly driven by their naturally lower housing expenses; note, however, that these are not zero and can be substantial (102€ on average). These costs are those of occasionally sleeping in shelters, hotels, or third party places, which are not necessarily free. Perhaps surprisingly, despite vastly different incomes and expenses, the rest for living of recipients – income minus expenses – is fairly similar regardless of housing status (331€ for the homeless, 329€ for private tenants, and slightly larger but not much more so, 373€, for social housing tenants);[27] we return to this finding below.

Finally, there is a fairly high exit rate from the sample. On average, about half (51%) of the recipients return to RDC a year from today. That is, poverty or, more accurately, food insecurity (as defined by presence in our sample) is a relatively transient state: The average duration of a spell is 18 months. The homeless are even less likely to remain in the RDC sample next year (43% survival rate, or an average spell duration of 14 months). Social housing tenants are the most likely to remain in the sample, with a 56% survival rate. Recall that exits from the sample can be due to various factors: people "getting back on their feet" is a likely explanation; we already discussed that deaths affect only a small share of homeless individuals in our sample, and migration outside of France is mitigated by the fact that we are focusing the analysis on French residents; it is also possible, though difficult to quantify, that some recipients drop out of the sample because they prefer to go to another charity

[26] We construct this variable as a dummy equal to one if the household has a positive wage.

[27] The difference between the rest for living of social housing tenants and that of the homeless (resp., private tenants), 43€ (resp., 44€), amounts to 29% (resp., 59%) of the gap in their housing expenses.

or have access to a support network or enough resources privately. Note, however, that households reporting a past episode of homelessness or severe housing precarity in EU-SILC also typically describe these spells as short: about 70% state that the episode lasted no more than 12 months, implying that only around 30% remain in distressed housing conditions after one year.[28]

Non-Residents. For reasons of space, we provide the corresponding sufficient statistics for the subsample of non-residents in Appendix C.2. Table 11 shows that non-resident French households are young, mostly single, and largely excluded from the labor market. Figures 33 and 34 indicate that income remains extremely low throughout the life cycle, with "other income" and asylum support as the primary sources of resources. Figure 35 highlights strong heterogeneity in household finances across housing situations, with especially tight budget constraints for the small share of non-residents that accesses private tenancy. For these households, support from RDC represents a large and critical share of consumption – nearly matching their rest for living (or non-housing expenses).

2.5 Income and Expenses over the Life-Cycle

In this section, we provide further descriptive statistics on the finances – income and expenses – of households in our sample. As in the previous subsection, we focus here on the French residents; the corresponding analysis for non-residents is in Appendix C.2.

Overview of the Government Transfers. The main welfare benefit, already mentioned earlier, is the RSA, or "*revenu de solidarité active*". The RSA is close, though not strictly equivalent, to a universal basic income (i.e., the demogrant of the tax schedule). Similar to a UBI, it is only available when a household's income (including government transfers) is equal to zero.[29] Unlike a literal UBI, however, eligibility is subject to conditions: (i) recipients must be at least 25 years old, with exceptions for single parents with children; (ii) immigrants from the EU (resp., outside the EU) become eligible after 3 months (resp., 5 years) of residency; (iii) eligibility depends on an assessment of the individual's "lifestyle", including the value of

[28] Among those exiting such situations, 32% (resp., 22% for strict homelessness) report moving into social or subsidized private housing, 25% (resp., 38%) attribute their exit to gaining employment, 11% (resp., 20%) to renewed or newly formed family or partner relationships, and roughly a quarter cite other reasons. Entry into distress is most often triggered by relationship or family breakdown – reported by 42% (resp., 62%) – followed by financial hardship for 28% (resp., 17%), and other reasons for 20% (resp., 14%). Health problems play only a minor role, mentioned by just 2% in both groups. Of course, all of the caveats mentioned earlier about survey data also apply here.

[29] Equivalently, it is distributed "universally" but is phased out through taxes at positive income levels.

their real estate, vehicles, appliances, vacation, etc. The RSA amounts to 646€ per month in 2025 for a single individual with no children. Unemployment, disability, or child benefits are deducted from the RSA allowance, while housing subsidies reduce it by a fixed amount (78€ for a single individual). The RSA is phased out – after a three-month lag – once an individual earns an income.[30]

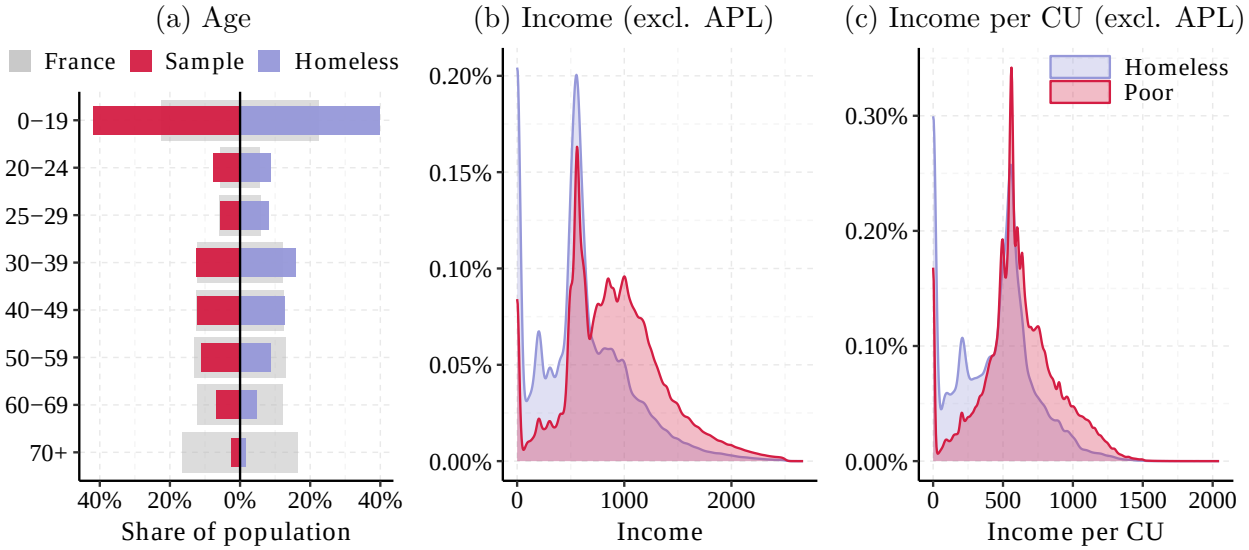
The other welfare benefits to which individuals in our sample have access include: the employment bonus ("*prime d'activité*", similar to the EITC in the U.S.); unemployment benefits (ARE, "*allocation de retour à l'emploi*"); long-term unemployment assistance (ASS, "*allocation de solidarité spécifique*", available when unemployment benefits run out); housing subsidies (APL / ALS / AFL, "*aide personnalisée au logement*", which is also available for homeless individuals but is given directly to shelters); child benefits ("*allocations familiales*"); old-age benefits (ASPA, "*allocation de solidarité aux personnes âgées*", a floor on pensions available above age 65, equal in 2025 to 1,034€ per month minus other income); disability benefits (AAH and ASI, respectively "*allocation adulte handicapé*" and "*allocation supplémentaire d'invalidité*"); and, for non-residents, asylum support ("*allocation demandeur d'asile*").

Age and Income Distributions. Figure 32 shows the distributions of age (left panel) and income (total household income in the middle panel and per CU right panel), both for the overall sample (red) and for the homeless (blue). Note that we report the distributions of income excluding housing subsidies (and correspondingly adjusting the RSA level), as explained in the previous subsection. The income distribution has clear bunching masses at the RSA amount – around 600€ per CU depending on the structure of the household. There is also a bunching mass at 0 income, which reflects a combination of (i) non-eligibility to transfers; (ii) non-take-up of welfare benefits; (iii) potential misreporting. Given RDC's reporting requirements, the first explanation is the most likely: recall that the RSA is subject to an age requirement, so that many RDC recipients younger than 25 (e.g., students) are ineligible. We study in more detail the population reporting zero income, along with the reasons that might explain incomplete take-up of transfers, in Appendix C.1. Finally, homeless recipients are younger and have much lower incomes on average.

Income Over the Life Cycle. The left panel of Figure 7 gives a decomposition (in our resident sample) of the average monthly income along the life-cycle into its main components: labor income, pensions, government transfers, alimony received, and "other regular

[30]The precise rules of eligibility and amounts depend on several variables and can be computed here. Further details are available here.

Figure 6. Distributions of age, income per CU, and income per CU without housing benefits



Note: For comparison, the counterpart distributions for non-resident French households are reported in Appendix C.4, Figure 31.

income". As noted earlier, this figure combines extensive- and intensive-margin values; the corresponding amounts conditional on receiving each payment are shown in Appendix C.4. Consistent with Table 1, we first notice that wages are only a small fraction of household income – on average 100€ per month per working-age individual. This is much smaller than welfare benefits, which account for the largest share of the revenues between ages 25 and 60: about 450€ per month on average.[31] The minor importance of wage income, especially in comparison to the U.S. where there is a large number of "working poor", may partly reflect the relative generosity of welfare benefits, but also – and possibly primarily – a sclerotic labor market: the overall unemployment rate is above 7.5% in 2025, while the youth (below age 24) unemployment rate is close to 20%.

The right panel of Figure 7 gives the decomposition of welfare benefits – the main category of income below retirement age – into its main components, per consumption unit. The RSA accounts for the largest share of transfers, amounting to between 150€ and 200€ on average among the 20-60 year old population. This is smaller than the statutory amount would suggest, because the RSA is reduced by the amount of other incomes (including transfers) that a household receives, as explained above.[32] The housing subsidy is roughly

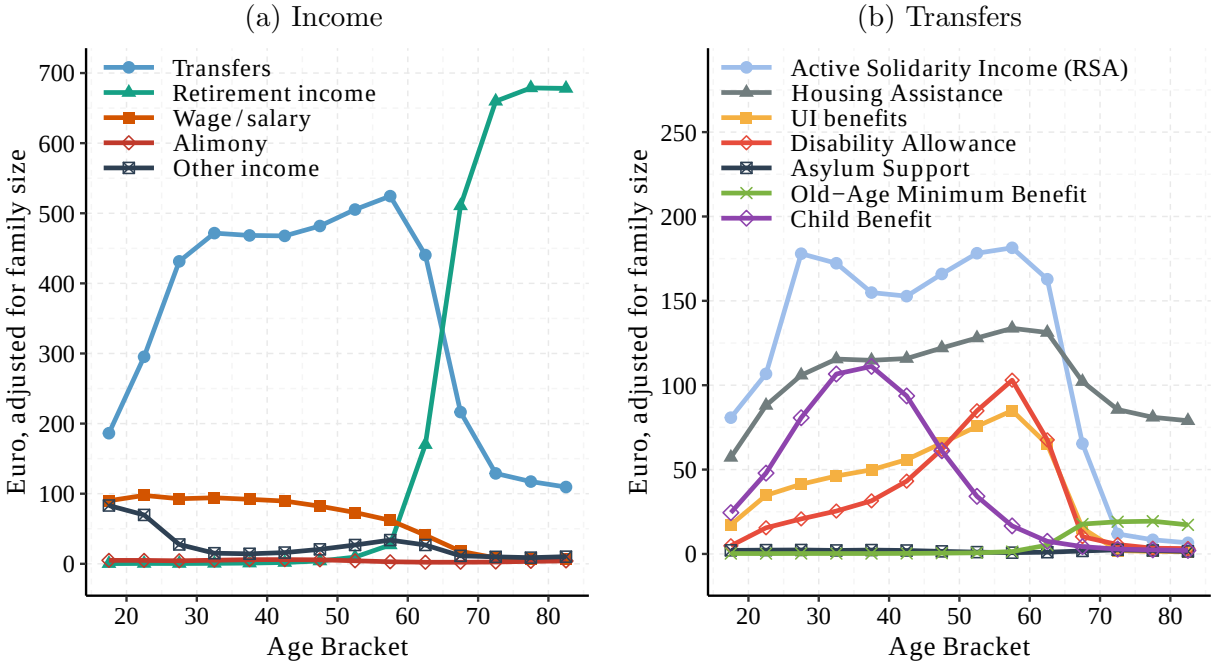
[31] Notice that, while the RSA transfer only kicks in at age 25 for most people, younger individuals in our sample do not earn higher wages. Instead, the category "other income" is significantly higher before age 25 – as high as wages – and drops when RSA eligibility starts.

[32] Thus, the fact that the sum of all incomes for the working-age population is roughly equal to a constant amount per CU (about 600€), regardless of age and of the decomposition of the transfers, arises by design

constant over the life cycle, although smaller for young households, who are more likely to be homeless. Child benefits are, unsurprisingly, largest for middle-age adults, while UI and disability benefits peak for older workers a few years before retirement.[33] Finally the old-age minimum pension benefit accounts for only a small fraction of retirees' income.

Both wages and welfare benefits drop past age 60, at which point pensions take over and reach about 650€ around age 70. It might be surprising that pensions are so high even though wages during working life are so low, and that the minimum pension benefit is not binding for most retirees even though it is nominally higher than the RSA, which is the main source of income for working-age individuals. There are two reasons explaining this: first, pensions are a reflection of lifetime incomes, whereas current income flows in our population may be the temporary outcome of a particularly bad year; second, those receiving pensions today are the baby-boomers who were more likely than the currently active cohorts to be employed during *their* working life several decades ago.

Figure 7. Decomposition of average income (left) and transfers (right) over the life cycle



Note: The two plots display unconditional average. Conditional counterparts, computed only among workers, disabled households, indebted households, and RSA recipients, are reported in Appendix C.1.2. For comparison, the corresponding unconditional average results for non-resident French households are reported in Appendix C.4, Figure 33.

rather than by coincidence.

[33]The duration of UI benefits increases progressively from 24 to 36 months above age 53.

Spending Over the Life Cycle. The left panel of Figure 8 reports the main household expenditures that we observe in our data: housing expenses (rent, utilities, and other expenses equal to the sum of mortgage and housing or property taxes), debt repayment, and alimony due. The largest of these expenses is rent: It grows from 150€ on average at age 20 to 300€ above age 70. Average debt repayment is small; recall from Table 1 that only a small share of the individuals in our sample have loans.[34] The right panel of Figure 8 constructs total housing consumption (the sum of rent or mortgage, utilities, and taxes), and non-housing consumption or rest for living (defined as income minus all recorded expenses). Finally, RDC also gives us the number of times a recipient came to collect food during the period. We use this information to compute a monetary value of consumption within RDC, based on what it would cost the beneficiary to obtain an equivalent basket from a regular store.[35]

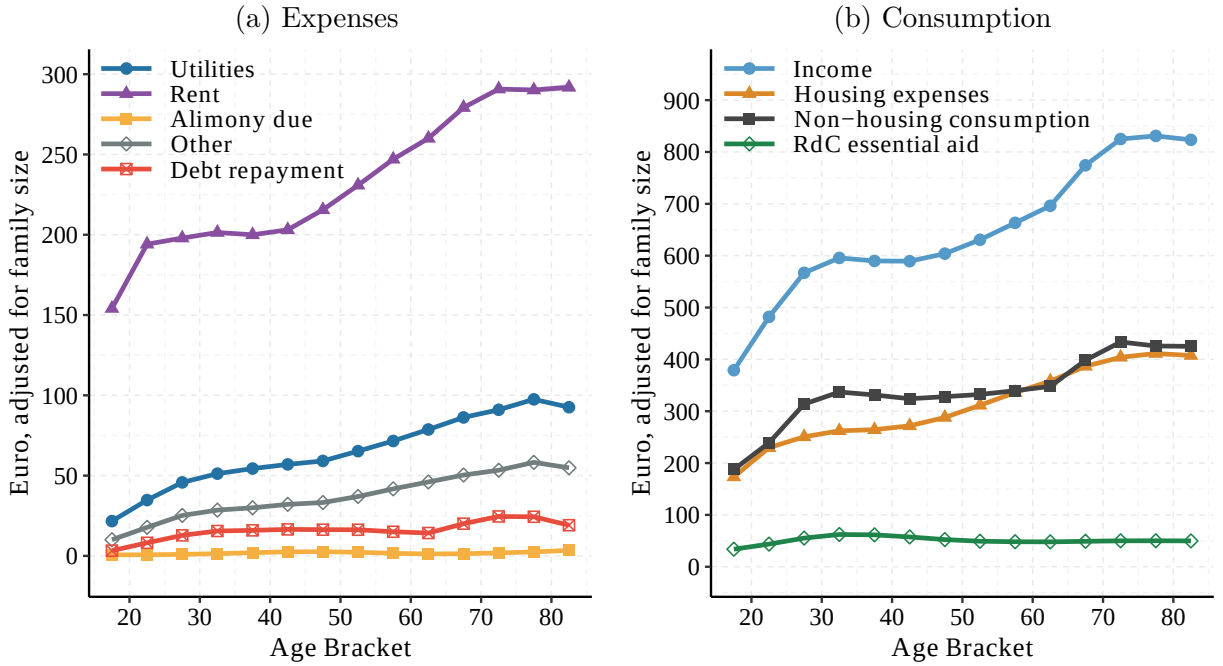
Rest for Living Over the Life Cycle and by Housing Status. Figure 9 shows the life-cycle evolution of (median) income on the left panel, (median) expenses on the middle panel, and (median and quartiles of) rest for living, or non-housing consumption, in the right panel, all split by housing status. The left panel shows that the median income is highest among the private tenants, closely followed by the social housing tenants, then the strict homeless, then (perhaps counter-intuitively) the broad homeless; homeowners have a non-monotonic income profile, with a severe mid-life decline and a recovery after retirement age due to pensions. The middle panel shows that housing expenses follow a similar ranking – note in particular that the strict homeless have higher housing expenses than households facing more broadly unstable situations, consistent with the fact that the former spend nights at hotels or shelters, while the latter may be able to sleep for free with third parties.

Now take the difference between income and expenses to compute the rest for living, and again plot the median by housing situation. The right panel suggests a striking pattern, which suggests that for the poorest households, housing appears to be a luxury relative to other basic needs. At any age, households in our sample spend almost the same amount regardless of their housing situation – around 350€ per person-month – for food and other basic necessities aside from housing. That is, non-housing expenses are remarkably stable at

[34] While we do not observe whether some individuals went through a personal bankruptcy procedure to have their debt erased, the Banque de France estimates that French households filed about 135,000 bankruptcy requests in 2024, about 10% more than in 2023, reflecting the consequences of the post-Covid inflation episode, but 40% less than in 2014, reflecting a stricter regulation of consumer credit along with a decline in unemployment.

[35] Specifically, we use the detailed list of products available to individuals each week to reconstruct an equivalent retail price bundle.

Figure 8. Decomposition of average expenses (left) and rest for living (right) over the life cycle

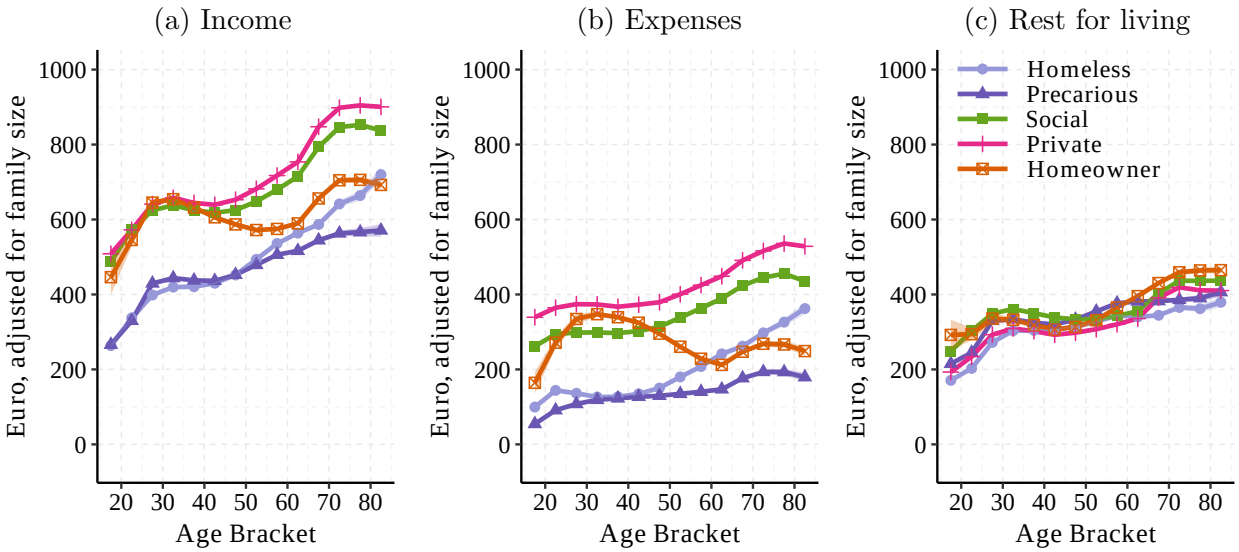


Note: The two plots display unconditional averages. Conditional counterparts, computed only among workers, disabled households, indebted households, and RSA recipients, are reported in Appendix C.1.2. For comparison, the corresponding unconditional average results for non-resident French households are reported in Appendix C.4, Figure 34.

this level, while any extra income above this subsistence amount appears to go almost one-for-one into higher housing expenses – either on the extensive or the intensive margin. This basic level of income is also fairly robust across ages except below age 25, i.e., until individuals are eligible for the RSA; these younger individuals are, apart from the few homeowners, unable to sustain the same subsistence level of non-housing consumption as their older peers. Finally, Figure 25 in the Appendix shows that a very similar pattern holds at the other percentiles of the distribution of rest for living, except at the very bottom.

Of course, these findings are only suggestive as they do not control for any covariate. We explore the substitution patterns between housing and non-housing consumption, both on the intensive and extensive margins, more thoroughly in Section 4.5.

Figure 9. Life cycle average income, expenses, and rest for living by housing situation



Note: For comparison, the counterpart results for non-resident French households are reported in Appendix C.4, Figure 35.

3 Econometric Specifications

The rest of the paper is devoted to understanding the exposure of the extreme poor to economic and policy shocks, along with the margins along which they adjust their consumption in response to such shocks. Because our sample may suffer from endogenous selection, we rely on an instrumental variable strategy to estimate these relationships. The first stage, which is of standalone interest, quantifies the drivers – local economic conditions, government policies, and individual characteristics – of entry into and exit from food insecurity or homelessness. The second stage exploit exogenous variation in these flows to identify the impact of economic shocks on the trade-off between housing, non-housing, and within-charity consumption.

3.1 Entry into Homelessness and Food Insecurity

We start by exploring the impact of local economic shocks on the probability of entering deep poverty.

Entry Model. We define the entry rate into homelessness (resp., food insecurity) in canton j and period t as the number of newly homeless (resp., in-sample) households, scaled

by the total number of households in that location.[36] Denote these probabilities of entry into homelessness and the sample by $EN_{jt}^{\text{homeless}}$ and EN_{jt}^{sample}, respectively, and let $\overline{EN}^{\text{homeless}}, \overline{EN}^{\text{sample}}$ denote their average over time and across cantons.

We then relate these local entry rates to changes in local characteristics using a linear probability model: for $\eta \in \{\text{homeless}, \text{sample}\}$,

$$\frac{EN_{jt}^{\eta}}{\overline{EN}^{\eta}} = \mathbf{X}_{jt}^{\text{local}} \cdot \boldsymbol{\beta}^{\text{local}} + \gamma_j + \delta_t + \varepsilon_{jt} \tag{1}$$

where $\mathbf{X}_{jt}^{\text{local}}$ is a vector of local characteristics described below. Unless explicitly stated otherwise, these independent variables are all measured in logs, so that – by virtue of the normalization on the left-hand side – the coefficients $\boldsymbol{\beta}^{\text{local}}$ can be interpreted as elasticities of the entry rate with respect to the corresponding local covariates. We report the results of the regression (1) weighted by the population of the canton.[37]

The period (e.g., "winter 2023") fixed effect δ_t captures the nationwide time trend in the entry rate. The location fixed effects γ_j absorb time-invariant differences across cantons. More precisely, we define a location as canton × season (summer or winter); that is, (say) Paris in the summer is treated as a different place than Paris in the winter. Finally, all the transitions we are studying are on a yearly basis, i.e., we compare a given winter wave of our sample to the previous winter wave, and similarly for summer waves.

The vector of local characteristics includes the numbers of active and retired households, the unemployment rate, the average income, food prices (at the département level), private and social housing rents per square meter, the number of private rental listings, the stock of social housing units, the capacity of homeless shelters, the stock of firms, the creation of sole-proprietor and other firms, the shares of various industries, and average temperature and rainfall. We also add the following interaction variables: unemployment times food price, unemployment times private rents, unemployment times social housing stock, and food price times social housing stock. These variables inform us about whether places with higher prices or rents are more sensitive to variation in the unemployment rate, or conversely whether a larger stock of social housing provides insurance against unemployment or inflation spikes.

[36] We do not treat households who were already homeless but moved in from another location into canton j as entrants.

[37] By assigning greater weights to cantons with larger populations, we reduce sampling noise and ensure that estimates are not driven by small areas with volatile entry and exit rates. Moreover, this specification better approximates the individual probability of entry than the unweighted specification that treats each canton identically. For robustness, we also report the results of the unweighted regressions in the Online Appendix.

Finally, we also control for the number of RDC centers per household in every location; this will be one of our instrumental variables in subsequent regressions, for which equation (1) will be the first stage.

3.2 Exit from Homelessness and Food Insecurity

Next, we study the impact of local economic shocks and individual characteristics on the probability of exiting deep poverty.

Exit Model: Canton Level. We start by estimating a model similar to (1) for exits out of homelessness and poverty. The left-hand side is now the exit rate, defined as the fraction of RDC recipients in that location and time period who no longer appear in the next wave of the sample. Denote these probabilities of exit from homelessness and from the sample in canton j at time t by $EX_{jt}^{\text{homeless}}$ and EX_{jt}^{sample}, respectively, and let $\overline{EX}^{\text{homeless}}, \overline{EX}^{\text{sample}}$ denote their average over time and across cantons. We then estimate, for $\eta \in \{\text{homeless}, \text{sample}\}$,

$$\frac{EX_{j,t+1}^{\eta}}{\overline{EX}^{\eta}} \;=\; \mathbf{X}_{j,t+1}^{\text{local}} \cdot \boldsymbol{\beta}^{\text{local}} \;+\; \gamma_j \;+\; \delta_t \;+\; \varepsilon_{it} \tag{2a}$$

where time $t+1$ indicates the same month or season as time t (i.e., March or November) of the following year, rather than the subsequent wave of the sample. Note that for the local characteristics that are only available at yearly frequency, we use their value in year t (respectively, $t+1$) as explanatory variables for the probability of exiting the sample in the March (resp., November) wave of year $t+1$.[38]

Exit Model: Individual Level. Since we observe individuals before they exit, we can also run a regression at the individual rather than the canton level. Let $\mathbb{I}_{i,t}^{\text{homeless}}$ and $\mathbb{I}_{i,t}^{\text{sample}}$ denote respectively the indicator function equal to 1 if individual i is homeless or present in the sample at time t. We then estimate, for $\eta \in \{\text{homeless}, \text{sample}\}$,

$$1 - \mathbb{I}_{i,t+1}^{\eta} \;=\; \mathbf{X}_{j,t+1}^{\text{local}} \cdot \boldsymbol{\beta}^{\text{local}} \;+\; \mathbf{X}_{it}^{\text{indiv}} \cdot \boldsymbol{\beta}^{\text{indiv}} \;+\; \psi(\widehat{P}^{\text{sample}}_{\underline{j}(it),\,\underline{t}(it)}) \;+\; \gamma_j \;+\; \delta_t \;+\; \varepsilon_{it} \tag{2b}$$

where j is the location (canton $\times$ season) in which individual i lives in period t, $\psi(\cdot)$ is a third-degree polynomial, and $\widehat{P}^{\text{sample}}_{\underline{j}(it),\,\underline{t}(it)}$ is the probability of entry into the sample (estimated from the model (1)) in the canton $\underline{j}$ and at the time $\underline{t}$ at which the individual started their current spell.

[38] Alternative timing assumptions did not qualitatively modify our results.

The vector of household characteristics $\mathbf{X}_{it}^{\text{indiv}}$ includes demographic variables (age, gender, marital status, number and age of children, citizenship, education, disability, housing status), financial variables (income, housing subsidies, indebtedness dummy, RSA take-up, consumption within RDC), and duration-dependence variables (repeated spell dummy, duration of the current spell).[39] We interact the spell duration with the household's housing status (homelessness, social housing, private housing, homeownership) to estimate tenancy-specific duration dependence. Note that we use the household characteristics at time t as explanatory variables for the probability of exiting the sample in period $t+1$, since we do not observe them at time $t+1$ after they have exited the sample.

Including (a flexible function of) the household's predicted probability of entry at the start of their current spell, i.e. the probability of selection into the sample, in the right-hand side of (2b) allows us to control for potential sample selection by verifying whether locations where entry is more likely also have systematically different exit rates. We discuss this sample selection in greater detail in the context of the consumption model.[40]

3.3 Consumption Choices

We finally study how local economic shocks, individual characteristics, and marginal income changes affect households' housing statuses (extensive-margin choice), housing and non-housing expenditures (intensive-margin choices) as well as their reliance on the charity's support.

Extensive-Margin Consumption Model. We first estimate the probability that an household "chooses" a particular housing status (private tenancy, social housing tenancy, homelessness of housing instability, homeownership) on the local economic variables and individual characteristics. We denote by $\mathbb{I}_{it}^{\text{homeless}}$, $\mathbb{I}_{it}^{\text{private}}$, $\mathbb{I}_{it}^{\text{social}}$, $\mathbb{I}_{it}^{\text{owner}}$ the indicator functions

[39] With these duration dummies included as covariates, Model (2b) is a discrete-time survival model. To avoid left censoring issues, we only include observations for which the spell duration is known, i.e., spells which started at the earliest in the second period of our data (if an household is present in the first period (Winter 2017), we cannot know when the spell started and we set its duration to unknown). Contrary to a Cox model, right censoring concerns are mechanically handled by this discrete-time survival model, because it proceed period by period, and, in the last period of the data, the dependent variable (next period indicator, $\mathbb{I}_{i,t}^{\eta}$) is not observed. Note that we could also run a Cox survival model. Since we have many observations and only a few discrete duration possibilities, we prefer to run this discrete choice survival model which is more natural and flexible.

[40] Since we control for many observable characteristics and correct for the entry probability in the sample, we interpret the effect of the spell duration on exit as a scale-dependence effect of duration. Yet, it is possible that unobserved types (characteristics) that we cannot control for remain. With a limited number of repeated spells, it is hard to identify such unobserved types, but it will become feasible in the future when we will have more time periods.

equal to 1 if individual i at time t is homeless, private tenant, social housing tenant, or homeowner, respectively. We then estimate, for $\eta \in \{\text{homeless, private, social, owner}\}$,

$$\mathbb{I}_{it}^{\eta} = \mathbf{X}_{jt}^{\text{local}} \cdot \boldsymbol{\beta}^{\text{local}} + \mathbf{X}_{it}^{\text{indiv}} \cdot \boldsymbol{\beta}^{\text{indiv}} + \psi(\widehat{P}^{\text{sample}}_{\underline{j}(it),\underline{t}(it)}, \widehat{P}^{\text{surv}}_{it}) + \gamma_j + \delta_t + \varepsilon_{it} \tag{3a}$$

where the vectors $\mathbf{X}^{\text{local}}, \mathbf{X}^{\text{indiv}}$ contain the usual location and individual covariates. Analogous to the regression (2b), we add a flexible function $\psi(\cdot)$ of the probabilities of entry and survival into the sample as a covariate. As in Section 3.2, this allows us to control for selection into the sample, as we explain in more detail below.

Intensive-Margin Consumption Model. Next, we evaluate the impact of local and individual covariates on the household consumption choices (housing expenditures, non-housing expenditures, and RDC reliance) conditionally on housing status. We thus estimate the following four regressions: for $\eta \in \{\text{homeless, private, social, owner}\}$,

$$C_{it}^{\eta} = \mathbf{X}_{jt}^{\text{local}} \cdot \boldsymbol{\beta}^{\text{local}} + \mathbf{X}_{it}^{\text{indiv}} \cdot \boldsymbol{\beta}^{\text{indiv}} + \psi(\widehat{P}^{\text{sample}}_{\underline{j}(it),\underline{t}(it)}, \widehat{P}^{\text{surv}}_{it}) + \gamma_j + \delta_t + \varepsilon_{it} \tag{3b}$$

where the outcomes C_{it} are the three consumption categories: housing expenditures, non-housing consumption or rest for living, and consumption within RDC.

Correction for Sample Selection: Instruments and Identification Assumptions. One concern is potential selection of individuals into the sample. We might estimate biased impacts of individual and local characteristics on exits from poverty if individuals who are more likely to apply for food assistance at RDC are also more likely to choose a particular type of housing (in regression (3a)), or to spend more (or less) of their income in housing vs. rest for living for a given housing status (in regression (3b)).

To address these issues, equations (3a) and (3b) control for potential selection of households into the sample via the function $\psi(\cdot,\cdot)$. The first argument of this function, $\widehat{P}^{\text{sample}}_{\underline{j}(it)\,\underline{t}(it)}$, controls for the initial selection into the sample at the time and location of entry using the entry model (1). The second argument, $\widehat{P}^{\text{surv}}_{it}$, controls separately for each household's probability of staying into the sample from the time of entry to the current period t. This second "survival" probability in the current spell is computed using the estimated exit probabilities in each period and for each household i using the exit model (2b).[41] This correction is in

[41] Note that in principle, we could simply control for the probability of being present in the sample at time t for household i. However, this probability cannot be easily computed since our entry model includes only the aggregate local covariates (as we do not observe households before they enter). Absent a better

the spirit of semi-parametric sample selection models as in, e.g., Newey (2009).[42]

The key identifying assumption is that there must be some variables in the entry regression (1) that (i) affect the selection probability, i.e. the right-hand side of (3a) and (3b); and (ii) do not affect the consumption choices, i.e. the left-hand sides of (3a) and (3b), other than through their effect on the probability of entry (exclusion restriction). Similarly, there must be some variables in the exit regression (2b) that (i) affect the probability of (not) exiting the sample; and (ii) do not affect consumption choices, other than through their effect on the survival probability.

In our case, for all of the regressions in (3a)-(3b), we use as an instrument the number of RDC drop-in centers in a given location in the current period (recall that there are numerous openings and closings of centers, see the left panel of Figure 3). The identification assumption is that the local number of RDC drop-in centers in a given period significantly impacts the probability that an individual applies for RDC support in that period and location; but an individual who goes to a given RDC drop-in center does not make different consumption choices (either on the extensive or the intensive margin) depending on how many other drop-in centers are present in their canton.[43]

One might be worried that a positive correlation between the number of local RDC drop-in centers and the probability that an individual enters the sample reflects reverse causality, if RDC decides where to open new sites based on the local prevalence of poverty. We address this concern by including a location fixed effect and controlling directly for the lagged number of RDC drop-in centers in equation (1). Hence, we only need to impose that the *change* in the number of RDC drop-in centers in an area between time $t-1$ and t is not driven by an *anticipated* change in poverty in the area between time t and $t+1$.

In addition, for regression (3b) restricted to the subsample of homeless individuals, we use as additional instrumental variables the private and social housing rents, as well as the stocks of private and social housing units. The identification assumption is that the rents and availability of housing in a given location at time t do not affect the consumption choices of households that remain homeless. Analogously, we use the private rents, stocks

entry model, we thus prefer to separate the probability of entering the sample, computed using the entry regression of Section 3.1, from the probability of surviving after having entered, computed using the exit regression of Section 3.2, controlling separately via a flexible function for both probabilities.

[42] This can be viewed as a non-parametric Heckman (1979) correction that relies on instrumental variables and exclusion restrictions rather than requiring us to specify the distribution of the error terms of the regressions.

[43] The corresponding identification assumption in the exit regression (2b) is that conditional on the number of RDC drop-in centers in the *next* period $t+1$, the number of centers at time t does not impact the probability that an individual exits the sample in the *next* period $t+1$.

of private housing units, and homeless shelter availability, as instrumental variables for the regression (3b) restricted to the subsample of social housing tenants. And finally, we use the social housing rents and stock as well as homeless shelter availability as instruments for the regression (3b) restricted to the subsample of private tenants. The exclusion restrictions are again that conditional on selecting into a given housing status, the rents and availabilities in the markets for *other* housing types are irrelevant to the household.[44]

Non-Linear Effects of Marginal Income Changes (Engel Curves). We are particularly interested in the potentially non-linear relationship between income and housing consumption, both on the extensive and the intensive margins. The first relationship (extensive margin) measures the predicted share of households in different housing statuses (homeless, other unstable, social housing, private tenant, homeowner) at each level of income. These predicted shares are measured non-parametrically conditionally on all other individual and local characteristics. The second relationship (intensive margin) measures the impact of income on housing expenses, conditional on a given housing status (and all other covariates).

To compute the extensive-margin effect of income on housing status, we regress the latter on the former along with the usual (location and individual) covariates and the probability of being in the sample (in order to control for potential sample selection), exactly as in regression (3a). We run separate such regressions by splitting the income variable on the right-hand side into bins to estimate an average share of each housing status in all income bins. A potential issue, however, is that the household income (on the right-hand side of this regression) includes the housing subsidies (APL) that tenants may receive, which in turn affect how their RSA allowance is calculated. But these subsidies are, naturally, endogenous to the housing status of the household (on the left-hand side of the regression). To correct for this potential bias, we regress instead housing status on a counterfactual income measure, which is the income the household would receive *if* they were homeless – i.e., without APL subsidies but a higher resulting RSA transfer.

To compute the intensive-margin effect of income on housing expenses conditionally on housing status, we regress housing expenses on the counterfactual income variable (as described in the previous paragraph) interacted with each housing status, as in regression (3b). Again, we split the income variable into bins when estimating this regression. This

[44]For the exit regressions (2b) restricted to the homeless sample, the corresponding identification assumption is that the rents and availability of housing in a given location at time t do not affect the probability of exit from homelessness in the *next* period $t+1$ (conditional on the rents and availability of housing in $t+1$).

allows us to measure non-linear tenancy-specific relationships between income and housing consumption, at the average level of all other covariates. Finally, taking the derivative of these consumption-income relationships gives the tenancy-specific marginal propensities to consume housing with respect to income.

Price Elasticities of Consumption. Our last step is to construct elasticities of housing consumption, both on the extensive (tenancy choice) and intensive (expenditure conditional on housing tenancy) vary with macroeconomic variables. We focus on prices for now.

For the extensive margin elasticities, we start from the consumption regression (3a). Recall that the vector of local characteristics $\mathbf{X}_{jt}^{\text{local}}$ includes the log of private rents, social housing rents, and food prices. Thus, the corresponding coefficients in $\boldsymbol{\beta}^{\text{local}}$ are the semi-elasticities of tenancy choice (homeless, private, social, and homeowner) on these prices. We then transform these semi-elasticities into elasticities at the mean, or for the average household, by dividing them by the average predicted share of this particular housing status in the sample. For instance, letting $\eta =$ homeless in equation (3a) and β^{food} the coefficient on the food price covariate, we estimate

$$\mathcal{E}^{\text{ext}}(\text{homeless, food price}) = \frac{\beta^{\text{food}}}{\mathbb{E}[\,\mathbb{I}_{it}^{\text{homeless}}\,]}$$

where $\mathbb{E}[\mathbb{I}_{it}^{\text{homeless}}]$ is the average share of homeless recipients in the sample.

Next, we estimate the intensive margin elasticities, i.e., the elasticities of expenditures (housing, non-housing, and in-charity) with respect to prices. We start from the consumption regression (3b) on the subsample restricted to a given housing status (say, homelessness). The coefficient on the log-price covariates (say, the food price) give us the corresponding semi-elasticities of the dependent variable (say, housing expenses). We can then compute, within the homeless subsample,

$$\mathcal{E}^{\text{int}}(\text{housing, food price} \mid \text{homeless}) = \frac{\beta^{\text{food}}}{\mathbb{E}[\,C_{it}^{\text{homeless}} | \mathbb{I}_{it}^{\text{homeless}} = 1\,]}$$

where $\mathbb{E}[C_{it}^{\text{homeless}} \mid \mathbb{I}_{it}^{\text{homeless}} = 1]$ is the average housing expenditure in the subsample of homeless households.

4 Results

This section presents our estimates of the coefficients of regressions (1), (2a)-(2b), and (3a)-(3b). We use these estimates of the entry and exit regressions to elicit the role that the macroeconomic shocks which took place between 2018 and 2025 played in the staggering rise in homelessness in France during that period. In addition, we use the results of the consumption regression to estimate own- and cross-price elasticities of housing (on the extensive and intensive margins) and non-housing consumption.

4.1 Entry into Homelessness and Food Insecurity

Table 2 give the results of model (1), that is, the impact of local characteristics on the entry rates into (strict) homelessness, (broad) housing instability, and food insecurity as defined by presence into our sample.

Baseline Entry Rates. For reference, we first report the average flows into homelessness and food insecurity in the sample. For homelessness, there are 8.6 entries (or 0.31 per 1,000 households) per year, on average across years and cantons. Focusing on Paris – the largest canton – there are 393 entries into homelessness (or 0.26 per 1,000 households) per year. For overall food insecurity, the corresponding values are 88.8 entries on average per canton per year, and 1,711 entries per year in Paris alone.

Local Economic Conditions. First, Table 2 shows that the local labor market and broader economic conditions have a large impact on inflows into homelessness and food insecurity. Specifically, a 10% increase in the (broadly defined) unemployment rate (corresponding to a 2 percentage point increase, see Table 1) raises the entry rate into strict homelessness (resp., broad housing instability, food insecurity) by 8.9% (resp., 9.6%, 10.6%). That is, extreme poverty has an elasticity roughly equal to 1 with respect to the aggregate unemployment rate. Higher GDP per capita, proxied by the average local revenue, affects the entry rate negatively with elasticities ranging from -0.23 for food insecurity to -1.9 for strict homelessness. The point estimates on food inflation suggest elasticities of inflows into food and housing insecurity equal to 0.6. These effects are, perhaps surprisingly, marginally significant; this is because a large part of the variation in food prices is absorbed by the time and location fixed effects.[45] In sum, the sign of these coefficient estimates is unsurprising

[45] Regressing our département-level food inflation variable on département and time fixed effects gives an R^2 of 0.96.

Table 2. Determinants of Entry Rates: Effects of Local Covariates (Weighted)

	Homelessness		Unstable Housing		Poverty	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Log households	−6.341***	(1.825)	−3.270***	(1.050)	−11.308***	(3.881)
N RDC centers (per k hh)	2.616***	(0.880)	3.605***	(0.574)	5.643***	(0.539)
Log private rent	0.990***	(0.327)	0.110	(0.161)	−0.021	(0.091)
Log private listings (per k hh)	0.052	(0.193)	0.007	(0.107)	0.026	(0.042)
Log private rent (CAF)	—	—	—	—	0.836***	(0.211)
Log private housing number (CAF)	−0.651*	(0.386)	−0.235	(0.219)	0.158	(0.104)
Log social rent	−0.432	(0.271)	0.010	(0.172)	0.112	(0.109)
Log social housing stock (per k hh)	−0.927***	(0.240)	−0.254*	(0.135)	0.164*	(0.089)
Shelter capacity (per k hh)	−0.013	(0.009)	−0.003	(0.006)	0.001	(0.004)
Log unemployment	1.062***	(0.333)	0.956***	(0.192)	0.886***	(0.137)
Log food price index	0.596	(0.752)	0.276	(0.445)	0.620	(0.396)
Log local revenue	−1.955***	(0.633)	−1.105***	(0.359)	−0.229*	(0.131)
Log firm creation (sole propr.)	0.289***	(0.099)	0.020	(0.058)	−0.160***	(0.049)
Log firm creation (other)	−0.086*	(0.051)	0.001	(0.031)	0.047**	(0.023)
Log firm stock (per k hh)	−3.366***	(0.402)	−2.180***	(0.253)	−0.675***	(0.231)
Share manuf., mining & related	−2.958	(2.144)	−0.513	(0.775)	−1.999	(1.333)
Share construction	−0.588	(2.282)	−4.819***	(1.289)	−1.872**	(0.835)
Share wholesale, retail & food	0.092	(1.419)	−0.822	(1.292)	−2.356***	(0.698)
Share public admin. & health	−5.106***	(1.420)	−2.230**	(0.895)	1.709**	(0.744)
Log avg. temp. × Winter	−2.092***	(0.736)	−0.007	(0.558)	0.503	(0.430)
Log avg. temp. × Summer	2.354	(2.930)	2.670	(1.718)	0.587	(0.856)
Log rain × Winter	−0.152**	(0.063)	−0.119**	(0.037)	−0.066	(0.051)
Log rain × Summer	0.097	(0.088)	0.052	(0.056)	−0.012	(0.030)
FE: area × period	Yes		Yes		Yes	
Observations	20,507		20,601		21K	
Within R^2 (R^2)	0.035 (0.701)		0.029 (0.765)		0.049 (0.840)	

[a] Clustered (area_FE) standard-errors in parentheses. Signif. Codes: *: 0.1, **: 0.05, ***: 0.01.

(which is reassuring): namely, tighter labor markets, richer areas, or lower inflation rates are effective at reducing the likelihood of becoming homeless. The key contribution of our analysis consists of quantifying the magnitude of these effects.

Housing Market. Second, the housing market variables play a central role in explaining inflows into homelessness. Recall that we use two measures of private rents, one that gives those of units currently occupied by welfare benefit recipients (CAF) and another that gives the average market rent among currently listed vacancies. Legally, rents on existing leases can only be raised based on a nationwide index computed from the overall CPI.[46] The former measure is therefore the most relevant for private and social housing tenants, who are relatively well insulated from local variations in market prices. By contrast, rents on

[46] Source here.

new leases should be the most relevant variable for homeless households. Confirming this intuition, we find that a 10% increase in rents on new listings (from a baseline of around 13€ per square meter) raises the entry rate into homelessness by 9.9%, while a 10% increase in the rents of units currently occupied by low-income tenants (from a baseline of about 10€ per square meter) raises entry into the sample by 8.4%.[47] On the other hand, active housing policies seem to be efficient at reducing inflows to homelessness: Raising the stock of social housing units by 10% results in a 9.3% reduction in the entry rate. Social housing rents do not have a significant effect on entry flows, suggesting that the main policy margin to prevent homelessness would be to raise their quantity rather than further subsidizing prices.

Firms and Industries. Third, Table 2 shows that local firm dynamism and industry composition also play critical roles in explaining entry flows. The largest effect is that of the overall stock of firms: a 10% increase in the number of local businesses reduces entry into homelessness by a staggering 33.7%, and into food insecurity by 6.8%. Note that higher rates of creation of new sole-proprietorship firms are negatively (resp., positively) associated with entry into food insecurity (resp., homelessness), with modest elasticities. These effects may reflect the high failure rate of micro-enterprises or the fact that some poor households decide to become self-employed. The industry composition of a location also correlates very strongly with homelessness and food insecurity (although the estimates are noisy): entry into both homelessness and food insecurity is lower in areas with a larger prevalence of firms in manufacturing, construction and, for food insecurity, wholesale and retail trade, transportation, and hospitality services. These are presumably the industries that are large providers of low-skill jobs. The presence of public administration, education, health, and social services seems to also be a major factor reducing entry into homelessness (perhaps due to the support that they provide) but these are also positively correlated with entry into food insecurity – likely due to a reverse causality mechanism, if social services are more likely to be present in poorer areas.

Other Local Variables. The number of RDC drop-in centers in a canton has a large and significant positive impact on entry into the sample. Therefore, the first stage of our instrumental variable strategy, aimed at correcting the exit rates for potential selection into the sample by controlling for the probability of entry, is strong. Finally, climate variables affect entry into strict homelessness: both lower rain volume and colder winter temperatures raise entry, the latter possibly capturing the effect of higher heating costs included in the

[47] Controlling for prices, areas with a larger number of vacant private housing units (as measured by the number of listings) do not exhibit significantly more inflows into homelessness.

rent.

Interaction Terms. Last, we run separate regressions with the following interaction terms between unemployment, the food price index, private rents, and the social housing stock. The results are shown in Table 3.[48] We find that the marginal effect of unemployment on the homelessness entry rate depends significantly on food prices and rents: higher prices amplify the impact of unemployment on inflows, and vice versa. Thus, inflation and unemployment shocks compound one another. Furthermore, food and housing insecurity are, if anything, *more* sensitive to unemployment and inflation shocks in places that have a higher stock of social housing. That is, social housing does not seem to act as efficient insurance against recessions. Quite the contrary: it may even create poverty traps, perhaps due to committed housing expenditures – although it remains highly speculative at this stage, this could happen if tenants are reluctant to let go of their social housing unit (which are in short supply) when they are hit by adverse shocks.

Table 3. Determinants of Entry Rates: Main Effects and Interaction Terms (Weighted)

	Homelessness		Unstable Housing		Poverty	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Main effects (interacted variables)						
Log unemployment	−36.117***	(3.275)	−9.821***	(1.985)	−0.477	(1.360)
Log food price index	13.513***	(2.300)	2.019	(1.377)	−2.143**	(0.957)
Log private rent	5.336***	(1.464)	0.473	(0.874)	−0.485	(0.432)
Log social housing stock (per k hh)	−2.648***	(0.957)	−2.999***	(0.551)	−1.770***	(0.352)
Interaction terms						
log(unemp) × log(food price)	6.870***	(0.731)	2.123***	(0.429)	0.006	(0.290)
log(private rent) × log(unemp)	2.227***	(0.615)	0.179	(0.377)	−0.239	(0.184)
log(social stock) × log(unemp)	−0.114	(0.198)	0.085	(0.121)	0.424***	(0.100)
log(social stock) × log(food price)	0.492**	(0.247)	0.687***	(0.141)	0.631***	(0.094)
FE: area × period	Yes		Yes		Yes	
Observations	20,507		20,601		20,846	
Within R^2 (R^2)	0.080 (0.715)		0.041 (0.768)		0.053 (0.841)	

[a] Clustered (area_FE) standard-errors in parentheses. Signif. Codes: *: 0.10, **: 0.05, ***: 0.01.

4.2 Exit from Homelessness and Food Insecurity

We now focus on the determinants of exit rates from homelessness (strictly or broadly defined) and food insecurity more generally. Tables 4 and 5 report the estimates obtained

[48] We run these regressions separately so that the magnitude of the coefficients for all the other variables, expressed as elasticities, remain directly interpretable in the main table.

from canton-level exit regressions (equation (2a)) with and without interaction terms, while Table 6 gives the results of the household-level regression (2b). Some key coefficient estimates on household characteristics (age, income, and duration dependence) are represented graphically in Figures 10 and 11.

Baseline Exit Rates. For reference, we first report the average outflows in our sample. About 69.5% of the local homeless population exits homelessness each year on average across cantons (58% in Paris), while 52.4% exit food insecurity (44.8% in Paris.)

Table 4. Determinants of Exit Rates: Effects of Local Covariates (Weighted Canton-level)

	Homelessness		Unstable Housing		Poverty	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Log RDC population	0.063***	(0.008)	−0.197	(0.211)	0.069***	(0.010)
N RDC centers (per k hh)	−0.081	(0.334)	−0.776***	(0.183)	−0.110	(0.109)
Log private rent	−0.009	(0.106)	−0.047	(0.059)	0.017	(0.037)
Log private listings (per k hh)	−0.008	(0.026)	−0.004	(0.015)	0.022**	(0.008)
Log private rent (CAF)	—	—	—	—	0.169**	(0.063)
Log private rent number (CAF)	−0.084	(0.073)	−0.076*	(0.043)	−0.033	(0.026)
Log social rent	0.365***	(0.128)	0.142**	(0.059)	0.053	(0.042)
Log social housing stock (per k hh)	−0.116	(0.104)	−0.086	(0.063)	−0.039	(0.033)
Shelter capacity (per k hh)	−0.003**	(0.002)	−0.005***	(0.001)	−0.001	(0.001)
Log unemployment	−0.013	(0.101)	−0.068	(0.061)	−0.047	(0.034)
Log CPI	−0.221	(0.250)	−0.163	(0.169)	0.110	(0.116)
Log local revenue	−0.202	(0.177)	0.045	(0.094)	−0.055	(0.042)
Log firm creation (sole propr.)	−0.004	(0.033)	−0.032*	(0.018)	0.007	(0.012)
Log firm creation (other)	−0.024	(0.025)	−0.015	(0.013)	−0.016*	(0.007)
Log firm stock (per k hh)	0.096	(0.169)	0.120	(0.099)	0.015	(0.051)
Share manuf., mining & related	−0.190	(0.940)	−0.082	(0.299)	0.308	(0.235)
Share construction	0.183	(0.643)	0.527	(0.510)	0.596***	(0.209)
Share wholesale, retail & food	−0.113	(0.485)	0.100	(0.390)	0.229	(0.192)
Share public admin. & health	−0.585	(0.657)	0.506	(0.367)	0.401**	(0.194)
Log avg. temp. × Winter	0.057	(0.268)	−0.354**	(0.167)	−0.265***	(0.101)
Log avg. temp. × Summer	0.854	(0.786)	0.192	(0.489)	0.663**	(0.276)
Log rain × Winter	0.019	(0.018)	0.042***	(0.013)	0.021***	(0.007)
Log rain × Summer	0.008	(0.027)	0.006	(0.017)	0.025**	(0.012)
FE: area × period	Yes		Yes		Yes	
Selection control (poly.)	Yes		Yes		Yes	
Observations	10,738		15,801		17K	
Within R^2 (R^2)	0.021 (0.215)		0.040 (0.284)		0.038 (0.417)	

[a] Clustered (area_FE) standard-errors in parentheses. Signif. Codes: *: 0.1, **: 0.05, ***: 0.01.
[b] All covariates are lead variables one year ahead (at the time of exit).

Local Covariates. The most striking result from the exit regressions is that, in sharp contrast to their effects on entry, the location characteristics have hardly any impact on the

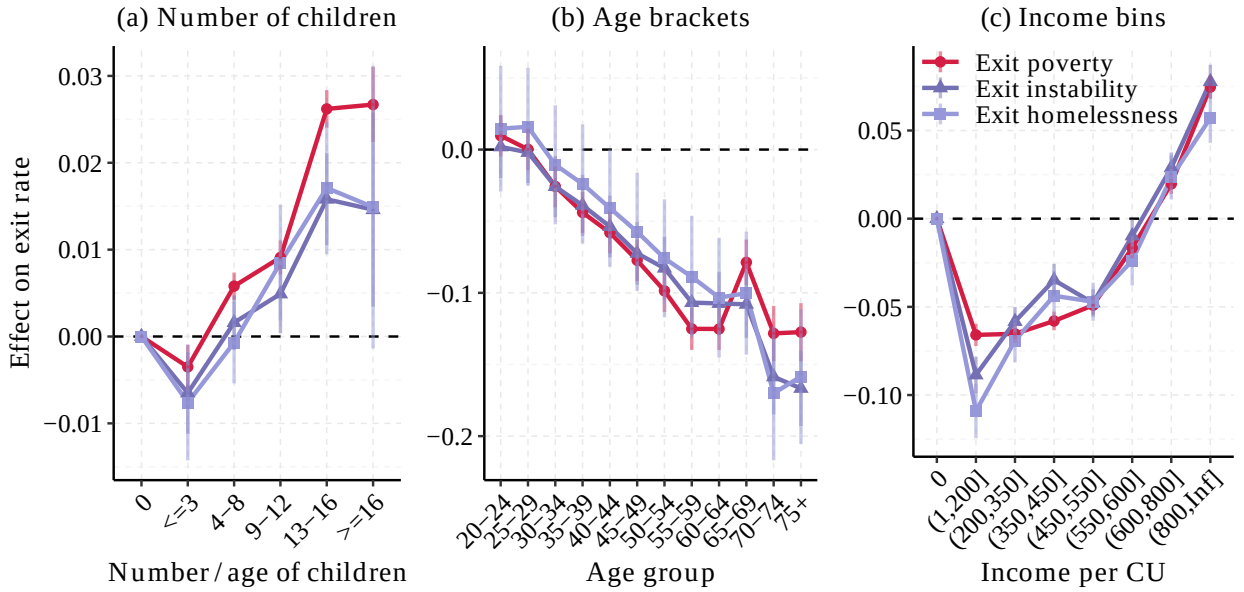
Table 5. Determinants of Exit Rates: Main Effects and Interaction Terms

	Homelessness		Unstable Housing		Poverty	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Main effects (interacted variables)						
Log unemployment	0.569	(0.800)	0.346	(0.540)	0.104	(0.320)
Log CPI	−0.693	(0.694)	0.063	(0.404)	0.232	(0.261)
Log private rent	0.402	(0.324)	0.054	(0.246)	0.223	(0.184)
Log social housing stock (per k hh)	−0.285	(0.322)	0.359*	(0.175)	0.089	(0.103)
Interaction terms						
log(unemp) × log(CPI)	−0.166	(0.178)	−0.103	(0.118)	−0.036	(0.077)
log(private rent) × log(unemp)	0.195	(0.145)	0.055	(0.104)	0.089	(0.074)
log(social stock) × log(unemp)	−0.065	(0.074)	−0.015	(0.045)	−0.053**	(0.026)
log(social stock) × log(CPI)	0.011	(0.081)	−0.106**	(0.044)	−0.054**	(0.024)
FE: area × period	Yes		Yes		Yes	
Selection control (poly.)	Yes		Yes		Yes	
Observations	10,738		15,801		17,013	
Within R^2 (R^2)	0.021 (0.214)		0.041 (0.284)		0.036 (0.416)	

[a] Clustered (area_FE) standard-errors in parentheses. Signif. Codes: *: 0.10, **: 0.05, ***: 0.01.

[b] All covariates are lead variables one year ahead (at the time of exit).

Figure 10. Determinant of Exit: Age, Income, and # Children



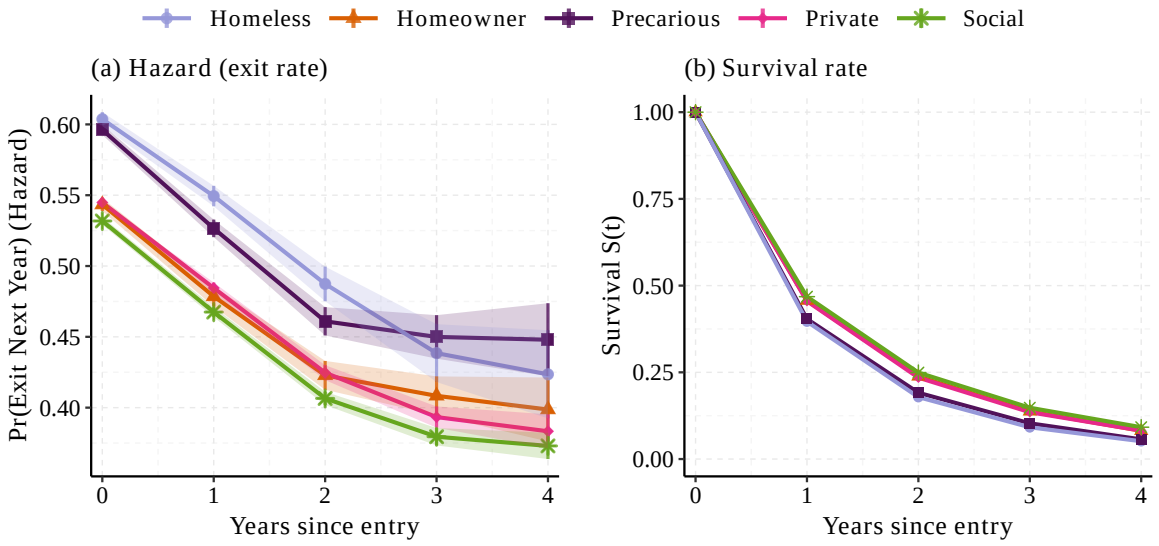
propensity to exit either homelessness or food insecurity. Most of the estimated coefficients are both statistically and economically insignificant. This insight is robust to all of the specifications that we have implemented. It holds both in the canton-level regression (Table 4) and in the household-level regression (Table 6), confirming that the stark difference with

Table 6. Determinants of Exit Rates: Household-level regressions

	Homelessness		Instability		Poverty	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Local covariates						
Log private rent	0.172*	(0.094)	0.130**	(0.059)	0.114***	(0.035)
Log private listings (per k hh)	0.021	(0.026)	0.000	(0.015)	0.009	(0.009)
Log private rent (CAF)	—	—	—	—	0.154**	(0.065)
Log private rent number (CAF)	−0.023	(0.061)	0.022	(0.041)	−0.012	(0.025)
Log social rent	0.019	(0.134)	0.002	(0.058)	−0.012	(0.036)
Log social housing stock (per k hh)	−0.060	(0.090)	−0.055	(0.057)	−0.019	(0.033)
Shelter capacity (per k hh)	−0.003**	(0.001)	−0.003***	(0.001)	−0.002	(0.001)
Log unemployment	−0.124	(0.077)	−0.185***	(0.052)	−0.075**	(0.035)
Log CPI	0.043	(0.219)	0.113	(0.152)	0.035	(0.102)
Log local revenue	0.006	(0.125)	−0.083	(0.080)	−0.002	(0.053)
Log firm creation (sole propr.)	0.031	(0.026)	0.034**	(0.016)	0.017*	(0.010)
Log firm creation (other)	−0.017	(0.019)	−0.005	(0.012)	0.008	(0.007)
Log firm stock (per k hh)	−0.202	(0.128)	−0.176**	(0.086)	−0.104**	(0.049)
Share manuf., mining & related	−0.516	(0.767)	−0.209	(0.289)	0.180	(0.246)
Share construction	0.702	(0.525)	0.110	(0.477)	0.182	(0.220)
Share wholesale, retail & food	−0.076	(0.464)	0.058	(0.372)	0.073	(0.178)
Share public admin. & health	−0.425	(0.527)	−0.049	(0.322)	0.024	(0.200)
Individual covariates						
Age + Income + # children	*see text and Figure 10.*					
Duration dependence	*see text and Figure 11.*					
Not first spell	−0.046***	(0.008)	−0.058***	(0.005)	−0.039***	(0.002)
Disabled	0.021***	(0.007)	0.000	(0.005)	0.006***	(0.002)
In debt	−0.010*	(0.006)	−0.014***	(0.004)	−0.017***	(0.001)
RSA take-up	0.023***	(0.004)	0.001	(0.002)	−0.008***	(0.001)
Rural (center)	−0.036*	(0.019)	−0.017**	(0.007)	−0.005	(0.004)
HH type: Single man (ref: couple)	0.004	(0.005)	−0.014***	(0.003)	−0.015***	(0.002)
HH type: Single woman	0.021***	(0.004)	0.006**	(0.003)	−0.014***	(0.001)
N children aged 0–3 (ref: none)	−0.007**	(0.004)	−0.006**	(0.003)	−0.004***	(0.001)
Nationality: EU (ref: French)	0.045***	(0.008)	0.034***	(0.006)	0.010***	(0.003)
Nationality: Other	0.035***	(0.004)	0.028***	(0.003)	−0.006***	(0.002)
Nationality: Unknown	0.037***	(0.006)	0.034***	(0.004)	0.034***	(0.002)
Education: N0 (ref: unknown)	−0.017*	(0.009)	−0.018**	(0.007)	−0.015***	(0.004)
Education: N1-N4	−0.003	(0.007)	−0.006	(0.005)	−0.006**	(0.003)
Education: N5-N8	−0.005	(0.012)	−0.009	(0.008)	0.007**	(0.004)
RdC consumption: 5–8 (ref: ≤5)	−0.077***	(0.004)	−0.078***	(0.003)	−0.090***	(0.002)
RdC consumption: 9–12	−0.127***	(0.004)	−0.134***	(0.003)	−0.151***	(0.002)
RdC consumption: 13–16	−0.219***	(0.005)	−0.242***	(0.003)	−0.272***	(0.002)
RdC consumption: 17+	−0.272***	(0.007)	−0.297***	(0.004)	−0.329***	(0.003)
FE: area × period	Yes		Yes		Yes	
Selection control (poly.)	Yes		Yes		Yes	
Observations	112,737		249,955		1,377K	
Within R^2 (R^2)	0.080 (0.135)		0.086 (0.126)		0.102 (0.125)	

[a] Clustered (area_FE) standard-errors in parentheses. Signif. Codes: *: 0.1, **: 0.05, ***: 0.01.
[b] All covariates are lead variables one year ahead (at the time of exit).

Figure 11. Determinant of Exit Rates: Duration dependence



Note: This figure reports the effect of duration × tenure in the individual exit model (2b). The reference group is private housing with a spell duration of 0 year. Instead of reporting only the coefficients of the effect of duration on exit rate, we report the hazard rates of exiting, computed simply by adding the average exit rate of around 54% to the duration-tenure specific coefficients. Note that the reported confidence intervals correspond to the confidence intervals around the duration coefficients, not around the predicted hazard rate. The second panel represents the survival curves derived from the hazard rates in the first panel.

the coefficients on entry rates is not an artifact of the different level aggregation.[49] Consider for instance the local unemployment rate: it is the only location-level explanatory variable that is marginally significant (though only in some of the regressions) for the probability of exiting housing instability or food insecurity. Even so, the corresponding point estimates are an order of magnitude smaller than those obtained in the entry regressions of Section 4.1.[50] We conclude that rising unemployment drives people into food insecurity and homelessness at much higher rates than falling unemployment lifts them out of these situations. All of the other local covariates are either extremely small (e.g., shelter capacity and firm stock) or statistically insignificant, or both.

[49]Notice that social housing rents appear to have significant coefficients in the canton-level specification, but their sign is the opposite of that one would expect: namely, higher rents tend to *raise* exit rates. We speculate that the counterintuitive sign of this relationship, which appears to be robust across specifications, reflects migration out of the canton, if higher rents push vulnerable households to relocate to more affordable locations. In any case, this effect disappears in the household-level specification.

[50]Translating the semi-elasticities into elasticity coefficients comparable to the entry elasticity counterparts of Table 2 requires dividing these estimates by the average exit rates from homelessness and food insecurity. Since we saw that these exit rates are of the order of 0.5, we obtain much smaller elasticities than for entries. We confirm graphically the minor impact of local variables on exits relative to entries in our counterfactual exercises of Section 4.4.

Individual Covariates. In contrast to the local economic conditions, individual covariates play a very important role in explaining exit flows from extreme poverty. Consider first the demographic variables in Table 6 and Figures 10-11. Age is a very strong predictor of exiting: The older the individual, the less likely they are to exit both homelessness and poverty. Recipients who are 50 or older have a 10 to 15 percentage point lower probability of exiting food insecurity or homelessness in the upcoming year relative to their 20–24 year old peers (recall that the average exit rates are around 50% overall). Single women are slightly more likely than men or couples to exit homelessness, but couples are the most likely to exit the sample. The effect of children varies with their age. Having a child younger than 3 years old reduces the odds of exiting both poverty and homelessness, likely due to the higher associated expenses. However, older children, and especially so the teenagers, have the opposite effect – perhaps reflecting a higher likelihood of being granted access to social housing. Disabled individuals are slightly more likely to exit homelessness and poverty, presumably due to their eligibility to disability benefits and potential priority access to social housing. Perhaps because of a higher propensity to move or migrate,[51] non-French EU citizens (among French residents) have a higher probability of exiting both homelessness and the sample than French citizens. Legal residents with non-EU citizenship are also more likely to exit homelessness, but they are less likely to exit the sample. Finally, education levels do not have a significant impact on exit rates out of homelessness, but exits from the overall sample are monotonically increasing with education.

Consider next the financial variables. Figure 10 shows that exit rates are monotonically increasing in income (including transfers) at strictly positive income levels: the higher the household resources per consumption unit, the more likely they are to exit homelessness or poverty in the following period. Specifically, having an income of 600–800€ per CU per month, i.e., around or slightly above the RSA allowance, raises the exit rates by 10 to 15 percentage points relative to those with less than 200€. This gap could result from the direct impact of higher resources, or reflect a selection effect based on unobserved individual characteristics – such as depression or lack of access to technology – driving both a reduced take-up of transfers and a smaller probability of exiting. Note finally, and perhaps surprisingly, that the exit rates from both homelessness and overall poverty are significantly higher for households who declare receiving zero income than for those with incomes as high as the RSA allowance. This is because in our sample of residents, individuals with no income are either those who are not yet eligible to receive the RSA, e.g. students younger than the

[51] Table 10 in Appendix summarizes the migration rates conditional on remaining in the sample.

minimum age requirement (typically 25), or those who have applied to the RSA allowance but not yet received a transfer. They are thus likely to become eligible and exit the sample in the subsequent period, explaining their high exit rates.[52] Finally, being in debt slightly reduces the probability of exiting both poverty and homelessness.

Third, our data exhibit a very strong duration dependence. We ask how likely an individual is to exit food insecurity, given that they have already been in our sample for 1 year, 2 years, etc. Figure 11 shows the results, for all categories of housing (at the time of first entry into RDC). We first observe that (controlling for all covariates) the homeless are the most likely to exit the sample a year from now, with an exit rate as high as 60% within the first year of the spell. They are followed by the private and social housing tenants (about 5pp lower exit probability) and the homeowners (7pp lower). The latter categories have presumably a lower ability to adjust their housing consumption on the intensive margin, leading to relative poverty traps caused by committed expenses (rents).[53] Second, we find that relative to the first entrants into the sample, and again controlling for all other covariates, spending 2 years into the sample reduces the probability of exiting food insecurity by 10 to 15 percentage points, regardless of initial housing status. The exit rate converges to about 45% for the homeless and 35-40% for the other housing categories after 3 years in the sample. That is, spending 3 years in rough housing yields a reduction in the probability of exiting extreme poverty (both food and housing insecurity) roughly equivalent to going from age 20-24 to age 70+, or from earning an income lower than 200€ to an income higher than 800€ per month. This extreme gradient far outweighs the impact of all other covariates. Experiencing a repeat spell – i.e., returning to RDC after having already entered and exited in the past – also reduces the probabilities of exiting homelessness and poverty by more than 4%.

Such strong duration dependence can be explained by a combination of factors. An individual who has spent years in extreme poverty might find fewer opportunities of exiting, e.g., due to loss of labor market skills, mental health issues caused by the experience of deprivation, etc. A supply-side explanation for the declining gradient of exits from homelessness is also possible, whereby individuals crave stability – the longer they remain homeless, the more difficult it becomes to upend their routine by changing their housing status. In that case, policy should aim at helping recipients out of homelessness as early as possible, and ensure that they are getting as much stability as possible with their potential accommodation.

[52] Figures 26 and 27 compare compare this group with those with higher incomes along several dimensions: age, family structure, occupation, citizenship, and duration at RDC.

[53] See, e.g., Chetty and Szeidl (2007, 2016).

Taking Stock: Asymmetric Effects of Economic Shocks. We have shown that entry rates into homelessness and poverty are strongly and significantly impacted by the local unemployment rate, the level of private housing rents, the stock of social housing, the stock of firms, and specific industries in the area. By contrast, none of these local characteristics seem to have any meaningful impact on exits out of extreme poverty. The key determinants of exit rates are, instead, individual- or household-level variables with, in particular, an extremely strong duration dependence. Thus, the impact of aggregate economic shocks is *asymmetric*: a recession causes a large inflow of individuals into housing or food insecurity, but a subsequent economic recovery does not help them escape this situation. This means that labor market and housing policies at the local level can prevent individuals from experiencing homelessness or poverty in the first place, but helping those who have already fallen behind requires individual-specific poverty alleviation mechanisms. What is more, these mechanisms should be implemented as early as possible in the individual's poverty spell, and aim to ensure the stability that several years spent in unstable housing might, paradoxically, provide.

4.3 Long-Term (5+ year) Food Insecurity

So far, we focused only on year-to-year exits from poverty. However, households may also return much later, or have regular exit-reentry patterns. In our sample ranging from winter 2017 to summer 2025, re-entries are actually quite infrequent, so that our year-to-year exit rates are the most relevant metric. We are also interested in measuring the proportion of long-run RDC recipients. Unfortunately, we do not have data before the 2017 winter campaign, but we have access to the yearly reports from the charity since 2009. For the winter 2012 and summer 2013 waves (henceforth the "2012-13" wave), RDC reported the number of individuals they served, as well as the percentage of individuals who entered for the first time in that year. In addition, our data give us the first entry of each individual with RDC. Therefore, we can estimate the probability of going to the charity at least once in the long run, defined here as 5 to 10 years after the first entry.

For the 432,000 first entrants in 2012-13, we find only 3.64% (15,696 individuals) apply for charity support at least once between the winter 2017 and the summer 2022 (5 to 10 years later), and only 3.37% are accepted for food assistance (14,576 individuals).[54] Compared to the sample of all households (including non-residents) during the same period, these

[54]The number of first entrants in $2012-13$ is, in fact, underestimated: these $432,000$ individuals are those who received food assistance at the time, thus it excludes individuals who applied but were denied support. Hence our numbers slightly overestimate the proportion of long-term persistence.

households are more likely to be French (63.5% vs 43.3%) and disabled (8.4% vs 5.9%). They are also (partly mechanically) older (51.5 years old vs 42.5 years old for the household head on average), and more likely to be retired (14.1% vs 7.2%). In terms of housing status, they are considerably more likely to be in social housing or private housing rather than in unstable housing: 49.5% vs 32.8% in social housing, 28.2% vs 25.1% in private housing, 9.5% vs 14.6% in precarious housing, and only 6.8% vs 23.5% strict homeless. This suggests again that long-run homelessness is in fact much less frequent than long-run food insecurity.

In the sample of all households present at least once between the winter 2017 and the summer 2022, the households who entered for the first time in $2012-13$ go on average to 4.46 waves (out of 10 over these 5 years), while the average household only goes to 2.47 waves. Part of this difference is mechanical though, due to the fact that the $2012-13$ first entrants are older.

4.4 Counterfactual Analysis

In this last subsection, we quantify the respective contributions of various economic shocks to the evolution of food insecurity and homelessness in France between 2018 and 2025. To do so, we use our estimates from the entry and exit regressions to compute the counterfactual evolution that would have occurred had a given explanatory variable remained fixed at its winter 2018 level, while letting all the others follow their actual course between 2018 and 2025.

Underlying Trends in Economic Variables. We start by describing the trends followed by several economic indicators during the 2018-25 period, aggregating the local data we used in the previous sections to the national level. The left panel of Figure 12 reports the behavior of food prices (green line); private rents (blue and orange lines, the former for newly posted listings, the latter for units currently occupied by welfare beneficiaries); and social housing rents (pink line). Food and rent inflation were both substantial, but took place at different times. Up to 2021, currently occupied housing (both private and social) evolved closely in line with the overall CPI (as intended), here proxied by food prices, but then kept their moderate inflation rate until 2023. By then, they had grown by a cumulative 5 to 8%. In stark contrast to this constant and moderate growth rate, food inflation picked up abruptly and very significantly after the pandemic – especially so in 2023 – to reach a 20% cumulative price increase over the five-year period. Finally, rents on newly listed units have seen almost as much inflation as food by 2023, but their evolution was more gradual and took place

in large part between 2019 and 2021, presumably reflecting the steep increase in housing demand during the pandemic years.[55] The middle panel focuses on measures of housing availability: the number of new private listings (green line) dropped by almost 40% between 2018 and 2023; again this mainly took place during the pandemic year, though it continued to fall in 2022 and 2023. The stock of social housing (pink line) remained unchanged throughout the period.

The right panel focuses on measures of economic activity: income (pink line); unemployment; firm creation (sole proprietorships in green, other firms in orange); and overall firm stock (blue line). Unemployment significantly declined in France since 2018, especially post-Covid (the official unemployment rate fell 9% in 2018 and 7.4% in 2023). At the same time, the overall stock of firms (per capita) jumped by about 20%, due to large increases in the creation of both sole-proprietor and other firms. This partly reflects the introduction of a new and successful business status in 2009, *auto-entrepreneur* (or "self-entrepreneurship"), with simpler administrative procedures and lighter tax regime, up to a cap on revenue. In 2018, the revenue cap doubled (to 170,000€ for sales of goods and 70,000€ for sales of services). This expansion led to a large increase in entrepreneurship. By 2023, there were about 1.9 million active self-entrepreneurs in France.[56]

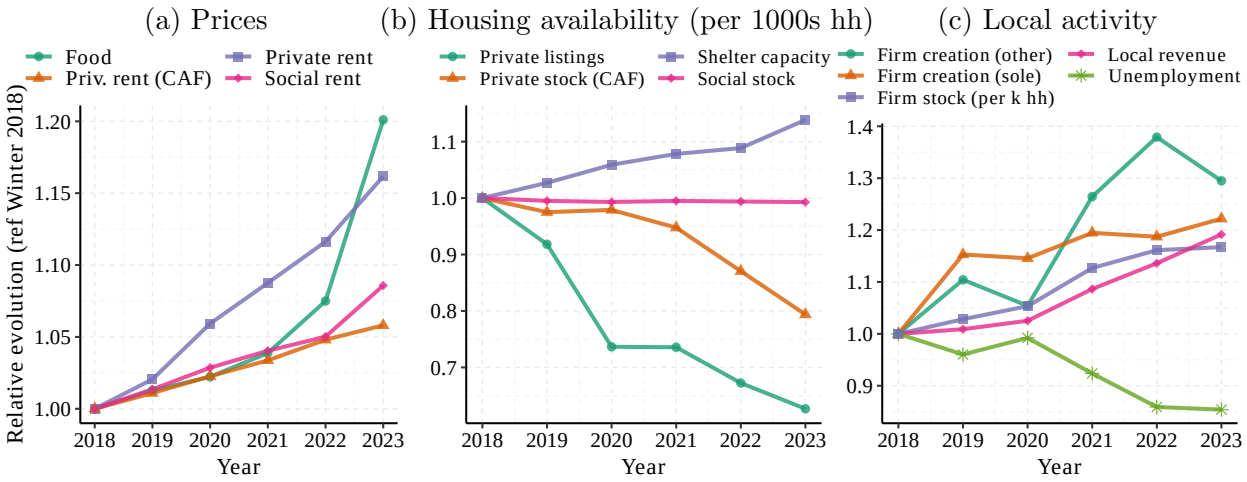
Note finally that active nationwide policies were implemented in 2020-21 in order to mitigate the negative consequences of the pandemic on poverty. Among others, these included extended employment protection (workers were able to reduce their labor supply while retaining their job and most of their earnings, while firms received direct subsidies to stay solvent) and housing affordability measures (the end of the "winter truce", or *trève hivernale*, during which evictions are forbidden, was postponed from March to July 2020, and from March to May 2021; gas and electricity were kept on in spite of unpaid bills; and households facing large income losses could receive temporary rent subsidies). These policies were implemented uniformly and should thus be mostly captured by the time fixed effect in our counterfactual exercises.

Results. Figure 13 reports the counterfactual evolutions of homelessness, broad housing instability, and overall poverty. Each line in these graphs keeps one the following variables fixed: economic activity (all firm-related variables, including industry composition); revenue; unemployment; prices (food price index, two measures of private rents, social housing rents);

[55] France was under nationwide lockdown between March and May 2020; in November-December 2020; and April 2021.

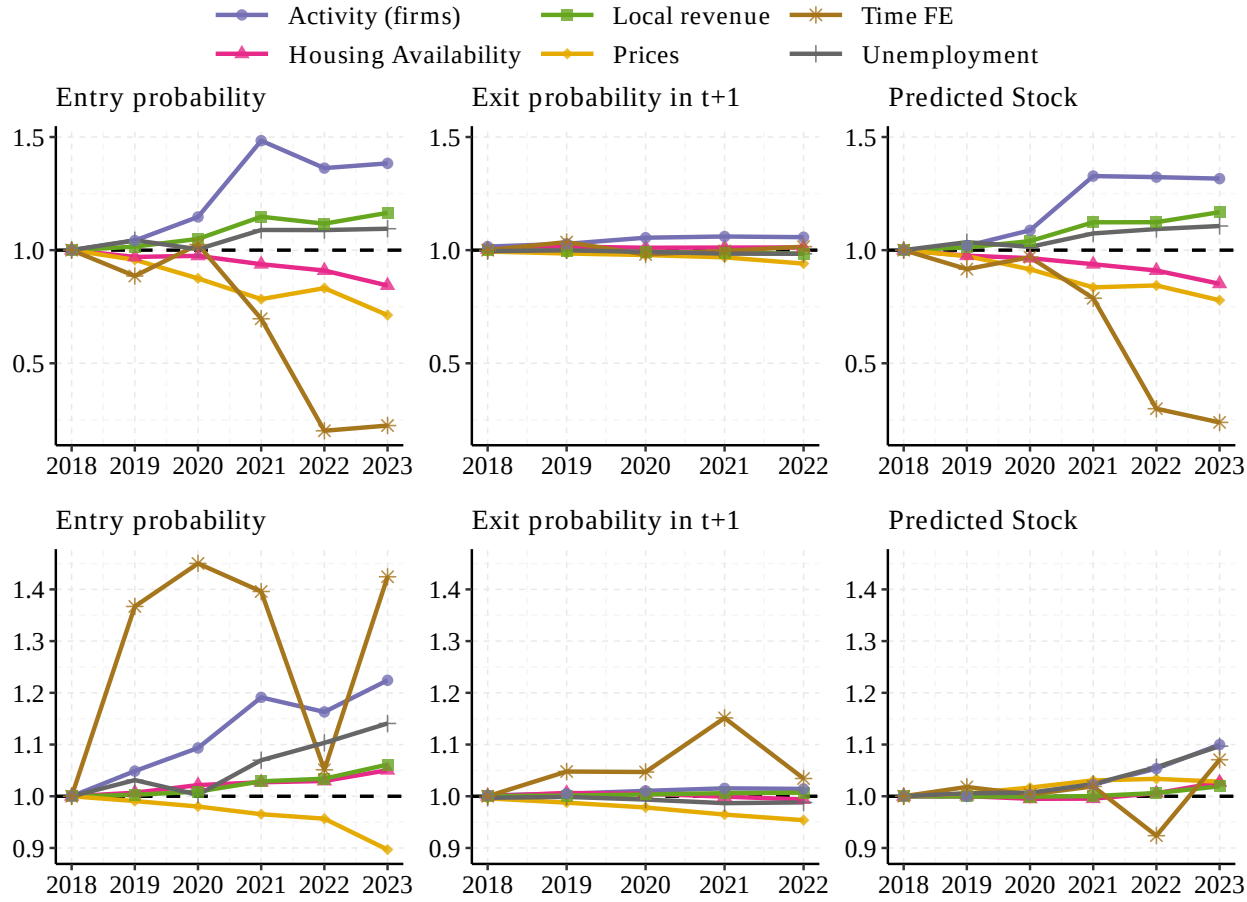
[56] Source: here.

Figure 12. Trend in economic variables



housing availability (private rental listings, stock of social housing units, shelter availability); and the time fixed effect.

Figure 13. Counterfactual dynamics excluding key drivers: Homelessness (Top) and Food Insecurity in general (Bottom)



Consider first the impact of the firm-related variables. If they had remained at their 2018 level, the entry rate into strict homelessness would have been around 30% higher than their actual level in 2023. In other words, the large amount of new firm creations after the pandemic significantly dampened inflows into homelessness; a similar finding holds for broader housing instability and food insecurity (i.e., presence in our sample). By contrast, exits would only have been only about 5% higher, consistent with the much smaller impact of local variables on exit rates that we uncovered earlier. These counterfactual flows imply a much higher (20%) stock of homeless individuals by 2024.

In contrast to these factors, the significant decline in unemployment since 2018 – despite its significant coefficient in the entry regression – played a smaller role in the actual evolution of homelessness: If it had remained fixed at its 2018 level, the overall stock of homelessness would have been 10% higher. Because they changed by a larger amount during the period, prices contributed to a larger extent to the evolution of homelessness. Absent rent and food inflation, the entry rate would have been much smaller, hardly mitigated by a slightly smaller exit rate (perhaps due to migration across cantons in response to high prices). As a result, had prices remained constant at their 2018 level, the overall stock of homelessness among French residents would have been close to 20% smaller.

Finally, the time fixed effect – which captures the contribution of factors that affected the whole country uniformly – also contributed to a large extent to the evolution of homelessness over the past decade. Two events clearly stand out: the Covid pandemic along with the nationwide policies aimed at mitigating its impact in 2020-21; and the subsequent sudden rise in inflation in 2022–23. Recall that the coefficient on food inflation that we found earlier only reflects the fact that some locations had different inflation rates than the national average; but the effect of the nationwide increase in prices is absorbed by the time fixed effect. We find that absent this fixed effect, inflows towards food instability would have been much larger in 2020-21 (+40%), while those into housing instability would have been substantially lower in 2022-23 (-35%). We conjecture that the lower-than-expected 2020-21 inflows into food insecurity reflect the impact of active policies aimed at mitigating the negative consequences of the pandemic on poverty. However, these policies were eventually phased out while inflation started rising in 2022-23. This led to a very sharp reversal, and a dramatic inflow of households into both food and housing instability. On net, these two events roughly offset each other for food insecurity: the overall stock of households facing food insecurity would have been roughly similar, absent the time fixed effect, by the end of

2022.[57] But the stock of households facing housing insecurity would have been about 30% lower absent the end of Covid-related policies and the 2022 nationwide rise in inflation.

4.5 Consumption Choices

We finally estimate the determinants of housing status (regression (3a)) and housing, non-housing, and within-charity consumption conditional on housing status (regression (3b)). The intensive-margin estimates from equation (3b) are collected in Table 8, while the estimates of the extensive-margin choices from equation (3a) are given in the Appendix (Table 12). Finally, Figure 14 represents graphically the non-linear impact of income on housing status and on the three categories of consumption. Our discussion in the main body of the paper focuses mostly on these Engel curves. We briefly discuss other covariates, and the price elasticities of housing and non-housing expenditures, at the end of this section.

Engel Curves and Marginal Propensities to Consume Housing. We start by quantifying the marginal propensities to spend on housing vs. non-housing out of income. These MPCs are key variables that macroeconomic models capturing the behavior of the extreme poor should aim to replicate. Recall that we consider separately the housing benefits (APL), debt repayments (if any), and the rest of the household income. We separate housing benefits from the rest of income in order to account for the endogeneity of the former to the level of housing expenditures that our regressions are trying to predict. As we explained Section 2.4, the measure of "income net of housing benefits" that we construct accounts for the corresponding adjustment to the RSA that the household would receive absent the housing subsidies.

Starting from the response of expenditures to housing benefits, Table 8 shows that they have a markedly different impact on homeless households vs. other recipients. The housing subsidy is clearly fairly fungible for private and social housing tenants: they spend about a third of it in housing (e.g., higher size, quality, or utilities) and the remaining two-thirds in non-housing expenses. By contrast, the strict homeless spend precisely 100% of their housing subsidies on housing, reflecting the fact that the allowance is typically given directly to shelters rather than as cash to the homeless individuals. Interestingly, the broadly unstable households spend *more* than 100% of their subsidies on housing and cut on their other

[57] A reversal takes place again in 2023. We suspect that this is due to the change in RDC's eligibility threshold, which no longer varies seasonally and thus became substantially lower in 2023. To the extent that it led to a decline in the number of accepted recipients into RDC, this policy change would be picked up by the time fixed effect and would spuriously suggest lower-than-expected entry rates into our sample.

expenditures, perhaps reflecting an effort to switch housing tenancy within the unstable category (e.g., from couch surfing to spending more nights at a hotel or shelter). The impact of debt repayment (conditional on being in debt) is the opposite: private and social housing tenants let non-housing consumption bear most of the burden of these repayments, while the homeless mostly pay back their debts mostly by reducing their housing expenditures.

Consider next the impact of income (net of housing benefits). The top-left panel of Figure 14 gives the extensive-margin impact of income on housing status, and the other panels give the average (over all other covariates) intensive-margin impact on housing expenditures (top right), non-housing expenditures (bottom left), and within-charity consumption (bottom right), conditionally on housing status. (Each point in these figures represent about a decile of the income distribution in our sample.) As expected, income quickly reduces the likelihood of being homeless, from about 60% at very low income levels to around 15% at the RSA allowance (about 600€ per CU) and 5% at 1,000€ per CU. The probability of being a private tenant follows a mirror evolution, starting at slightly above 10% among the poorest and reaching more than 45% for the richest individuals households. Finally, the likelihood of being in social housing is hump-shaped: It starts slightly above 20% for the very poor, peaks above 50% for households with incomes around 700€ per CU, and slightly declines thereafter.

On the intensive margin, a surprising and interesting pattern emerges.[58] Below 500€ of income, social and private tenants (as well as homeowners) have essentially a *zero* marginal propensity to consume on housing: after paying rent and utilities, amounting to about 200€ per CU for social housing tenants and 275€ for private tenants, all of their marginal euros of income are allocated to non-housing expenses. Homeless individuals (both strict and broad) have a positive but very low housing MPC, increasing their housing expenses by about 50€ between incomes of 0 to 500€ per CU, i.e., an MPC of 0.1. These patterns can also be seen in the bottom left panel, where the non-housing consumption (rest for living) increases one-for-one up to 500€ for all recipients.

Now, once they reach that income threshold (i.e., a rest for living of 200-300€ for tenants, and 450-500€ for the homeless), a structural break in the income–housing relationship arises. All households, regardless of housing status, start consuming a significantly larger share of their marginal income on housing. The MPC jumps from about 0.1 to 0.5 for homeless households, and from 0 to 0.3 for private and social housing tenants. (This structural break

[58] Figure 37 in the Appendix shows similar graphs for housing quantity, i.e., expenditures deflated by the local rents.

only arises for homeless recipients in the non-housing expenses in the bottom left panel.) While part of this effect may be caused by a mechanical selection effect stemming from the eligibility rules of RDC, according to which individuals with higher income are more likely to remain in the sample if their housing expenses are higher, this cannot be the whole story: first, the structural break takes place far below the eligibility threshold; second, the MPC of 0 at much lower income levels (on average, but therefore also for all recipients) is unaffected by this selection effect.

To conclude, these highly non-linear MPCs formalize the intuition from Figure 9 that housing is a luxury good: most households spend very little of their *marginal* units of income on housing up until a basic subsistence level, beyond which their housing share of expenditures jump to a significantly higher level. Note finally that the reliance on the charity is mostly unresponsive to income.[59]

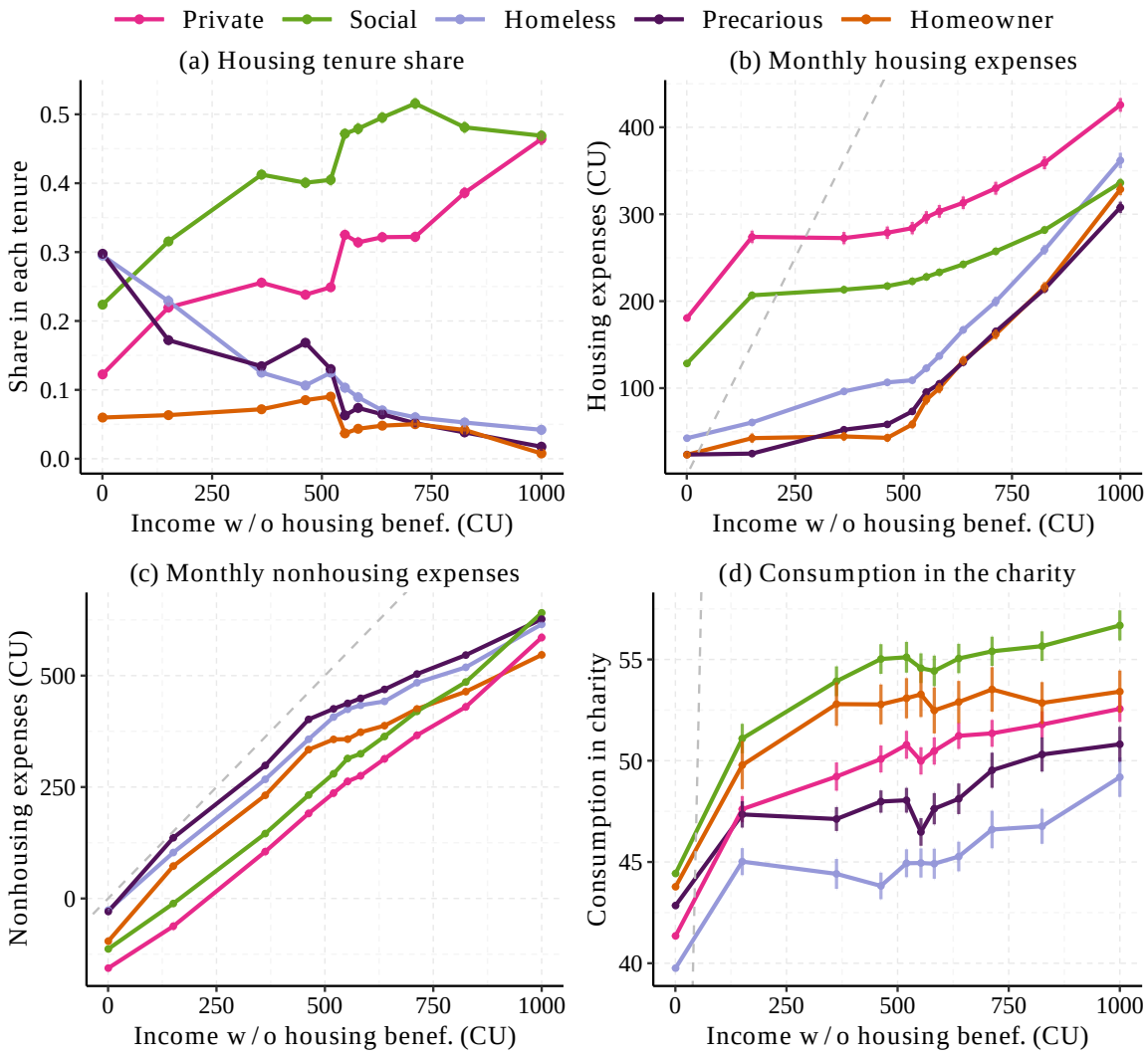
Price Elasticities of Housing and Expenditures. Finally, Table 7 report the elasticities of housing status (extensive margin) and expenditures conditional on housing status (intensive margin) with respect to rents and food prices and social housing availability. We focus on private rents in this discussion.

We find that private rents strongly reduce the probability of private housing tenancy, as well as (though to a lesser extent) non-housing expenditures. Quantitatively, as rents rise by 10%, a household is 2.7% less likely to be a private tenant, and those who remain renters spend 0.5% less on non-housing (while hardly changing their housing expenses). These intensive-margin estimates mean that almost all of the pass-through of higher rents is borne by the *quantity* of housing, keeping the overall spending unchanged in spite of higher prices: most of the higher housing costs are absorbed by reducing the size, quality, or heating of the apartment. These substitutions between different consumption categories are accompanied by a large increase in the reliance on food assistance: a 10% rent hike leads private tenants to consume 3.5% more within RDC.

As we already found in the entry regressions of Section 4.1, such rent increases heavily impact the probability of becoming homeless. A 10% rent hike raises the probability of being homeless (according to the strictest definition) by 11.8% (consistent with our estimates of

[59] If anything, it slightly rises with income. There are several potential explanations for this surprising finding, from heterogeneous preferences to heterogeneous likelihood of visiting other charities. We think a likely explanation is that the very low income households are those who just lost their job or faced a major hardship and have not yet received their transfers; such events can happen in between RDC waves, which would spuriously suggest that they go to an RDC drop-in center less often than their peers who signed up earlier in the season.

Figure 14. Predicted effect of income on consumptions and housing tenures



Note: this Figure reports the predicted effect of income without housing benefits (per CU) on (a) housing tenure shares, (b) monthly housing expenses (per CU), (c) monthly nonhousing expenses, or rest for living (per CU), and (d) consumption in the charity (in € equivalent per month). Note that the reported confidence intervals are *not* the confidence interval of the prediction, but only the confidence interval around the coefficients for the effect of income with respect to the baseline (of income equal 0) in each tenure-specific subsample. At a small risk of confusion, instead of plotting only the coefficients all starting from a 0 baseline when income equal 0, we plot the predicted outcomes directly since they provide more information.

Table 2). Interestingly, it also *reduces* by 5.4% the probability of broader categories of homelessness: this may be due to the fact that third parties such as family or friends are less likely to let homeless individuals stay at their place when their rent increases, perhaps because they can no longer afford it – or because they have become homeless themselves.

Finally, consistent with our entry regression estimates, a higher stock of social housing significantly raises the probability of being a social housing tenant, while correspondingly

reducing the probability of being homeless. Higher food prices increase all households' reliance on within-RDC consumption (note that we computed this consumption value in real, not nominal, terms).

Table 7. Elasticities (at the mean) with respect to prices and social housing availability

	Tenancy-specific subsample									
	Private		**Social**		**Unstable**		**Precarious**		**Homeless**	
Variables	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Elasticity of expenditures by housing status (intensive margin)										
					Outcome: Nonhousing expenditures					
Food price index	-0.10	(0.06)	0.19**	(0.06)	-0.02	(0.10)	-0.06	(0.10)	-0.03	(0.15)
Private rent per sqm	-0.05*	(0.02)			-0.19***	(0.04)	0.04	(0.04)		
Private rent per sqm (CAF)	0.09.	(0.05)			0.27***	(0.04)	0.29***	(0.09)		
Social rent per sqm			-0.07*	(0.03)						
Nb social housing per k hh			0.06**	(0.02)						
					Outcome: Housing expenditures					
Food price index	0.01	(0.05)	-0.12	(0.08)	-0.22	(0.24)	-0.26	(0.35)	-0.01	(0.33)
Private rent per sqm	-0.01	(0.02)			0.42***	(0.13)	-0.67***	(0.13)		
Private rent per sqm (CAF)	0.07.	(0.04)			-0.63***	(0.10)	-0.85**	(0.29)		
Social rent per sqm			0.10*	(0.04)						
Nb social housing per k hh			0.05*	(0.02)						
					Outcome: Charity Consumption (€ equivalent)					
Food price index	0.63**	(0.21)	0.97***	(0.17)	0.95***	(0.18)	0.93***	(0.20)	0.96***	(0.25)
Private rent per sqm	0.17*	(0.07)			-0.11**	(0.04)	0.12	(0.09)		
Private rent per sqm (CAF)	0.35*	(0.16)			0.16***	(0.05)	0.30	(0.20)		
Social rent per sqm			-0.17*	(0.07)						
Nb social housing per k hh			-0.12.	(0.06)						
Elasticity of each tenancy 'choice' of households (extensive margin)										
Outcome: Tenure =	Private		Social		Unstable		Precarious		Homeless	
Food price index	0.07	(0.13)	0.09	(0.12)	-0.43.	(0.24)	-0.03	(0.37)	-0.68	(0.49)
Private rent per sqm	-0.27***	(0.05)	0.01	(0.05)	0.37**	(0.11)	-0.54***	(0.14)	1.18***	(0.27)
Private rent per sqm (CAF)	0.49***	(0.10)	0.03	(0.09)	-0.83***	(0.20)	-0.47	(0.30)	-1.35**	(0.42)
Social rent per sqm	0.16*	(0.06)	-0.03	(0.06)	-0.12	(0.08)	0.25.	(0.14)	-0.48*	(0.22)
Nb social housing per k hh	-0.09.	(0.05)	0.23***	(0.04)	-0.27***	(0.08)	0.11	(0.12)	-0.69***	(0.16)

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.1$. This table reports elasticities at the mean household, obtained as described in Section 3.3, by dividing the semi-elasticities estimated in Table 8 by the appropriate sample-specific average outcome. Within unstable tenants, private rent affects only precarious tenants.

Other Intensive-Margin Consumption Estimates. The effect of all other covariates are collected in Table 8 (intensive margin) and Table 12 (extensive margin). Many of these estimates are interesting and deserve discussion – but this paper is already too long, and we leave it to the reader to interpret them.

Table 8. Determinants of expenditures (Housing, nonhousing and in charity) by housing status

	Private			Social			Precarious			Homeless		
Variable	Housing	Nonhousing	RDC	Housing	Nonhousing	RDC	Housing	Nonhousing	RDC	Housing	Nonhousing	RDC
Demographics.												
Age	*See Figure 36a.*											
Household type (ref: Couple)												
Single man	24.32***	-21.74***	-7.42***	21.01***	-17.40***	-8.11***	-24.79***	26.11***	-6.45***	-7.36***	6.37***	-10.58***
Single woman	40.23***	-40.50***	-5.82***	31.82***	-34.40***	-6.09***	-20.62***	22.26***	-4.55***	-4.47***	3.32***	-7.97***
Number of children...												
... aged 0–3	-26.11***	26.54***	30.73***	-20.42***	23.38***	31.86***	-9.12***	11.16***	32.94***	-15.33***	18.00***	34.10***
... aged 4–8	-16.92***	15.91***	7.90***	-13.75***	14.90***	8.59***	0.86.	-0.89	7.00***	-3.30***	4.36***	8.76***
... aged 9–12	-15.16***	14.32***	8.34***	-14.14***	15.16***	8.74***	0.48	-0.01	7.85***	-1.05*	3.32***	9.04***
... aged 13–16	-28.09***	26.71***	4.79***	-24.02***	25.85***	5.19***	4.27***	-4.60***	4.86***	-0.15	0.51	5.78***
... aged 16+	-32.33***	30.70***	3.47***	-27.65***	29.09***	4.14***	6.36***	-6.94***	3.62***	-0.77	2.08	4.08***
Citizenship (ref: French)												
EU citizenship	0.51	12.55***	1.45***	-0.51	7.82***	0.47.	11.60***	-9.85***	-0.79	11.49***	-9.20***	0.70
Other citizenship	-9.05***	22.44***	4.12***	-6.95***	16.14***	2.35***	21.33***	-19.11***	6.41***	5.09***	-1.72	6.17***
Unknown citizenship	6.65***	3.67***	0.66***	2.87***	4.35***	0.52**	4.93***	-1.93	1.15***	4.99***	1.68	2.73***
Student	13.28***	-4.58*	-2.08***	44.84***	-5.84	-2.45***	95.85***	-93.62***	-2.42***	144.39***	-143.71***	-2.41***
Retired	10.43***	2.21.	0.65***	11.06***	-3.08***	0.54***	-5.50*	-3.84	-2.11***	11.32***	-20.66***	-2.15***
Disabled	9.77***	25.04***	0.27*	5.14***	17.21***	0.32**	2.00	-7.69***	-1.40***	0.86	-5.78***	-2.65***
Duration in RDC.												
Not first spell	-13.27***	15.24***	2.14***	-4.18***	2.79***	2.66***	7.16***	-8.47***	1.81***	14.67***	-15.23***	0.69.
Spell duration in years	*See Figure 36b.*											
Finances.												
Income w/o housing benefits	*See Figure 14.*											
Housing benefits surplus (CU)	0.39***	0.65***	0.01***	0.33***	0.64***	0.01***	1.24***	-0.29***	0.01***	1.01***	-0.03*	0.01***
In debt	-10.11***	6.11***	-0.07	-6.73***	2.76***	0.16	-4.10**	-3.34*	-2.22***	-1.98.	-4.71***	-2.66***
Debt repayment (CU) if indebted	-0.10***	-0.72***	-0.00.	-0.05***	-0.79***	-0.01***	-0.26***	-0.62***	-0.00	-0.30***	-0.57***	-0.00
Local variables.												
Log food Price	4.14	-30.26	32.04**	-29.28	65.69**	53.52***	-20.58	-20.39	44.37***	-1.28	-7.99	43.32***
Log unemployment rate (%)	2.77	3.94	-10.20**	1.52	-3.26	-11.10**	-6.49	6.74	-13.19**	10.44	-1.79	-7.84.
Log local revenue	-13.76.	-11.21	1.51	-7.50	8.11	-3.50	7.73	-13.94	5.11.	-65.75*	64.05.	-0.39
Log firm creation (other)	-2.07.	-0.29	0.89	1.86.	1.23	0.58	-4.68*	7.49**	1.08	0.38	-0.85	2.61*
Log firm creation (sole-proprietorship)	-2.87.	-5.76**	-0.82	-4.14*	-3.88*	0.50	-0.27	-2.80	-0.30	3.61	-7.01	-0.77
Log private units (CAF) (per k hh)	-17.71**	15.06*	3.50	2.91	-5.57	-7.30*	9.25	-9.64	2.20	-6.38	30.23*	-1.38
Log private listings (per k hh)	2.09	2.77	-6.04***									
Log nb social listings (per k hh)				11.72*	20.94**	-6.36.						
Shelter capacity (per k hh)							0.05	0.47	0.22*	-0.21	0.49.	-0.04
Log private rent (ads)	-4.26	-16.93*	8.57*				-53.17***	11.67	5.81			
Log private rent (CAF)	23.65.	28.18.	17.86*				-66.87**	92.99***	14.52			
Log social rent				24.13*	-25.23*	-9.20*						
Urbanization (ref: City Center)												
Suburb	0.11	-1.43	0.85*	6.43**	-7.66***	0.08	-5.91**	5.10**	1.56**	6.46*	-7.15*	0.73
Isolated city	-1.01	-0.34	0.58	-0.27	-1.74	0.77	-3.90*	2.14	2.27***	-1.41	-2.59	2.93***
Rural	-5.55***	1.04	0.28	12.41***	-15.07***	-0.04	-7.01***	4.50*	1.64***	-7.13*	2.02	2.42***

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.1$.

This table reports the estimation of the tenancy-specific models (3b) for three types of expenditures (in € per month): (i) Housing expenditures, (ii) Nonhousing or rest for living expenditures, and (iii) consumption in RDC (expenditure equivalent). All models include (i) *period* and (ii) *canton* × *campaign type* (Winter or Summer) fixed effects. We also control flexibly for the probability of entering the RDC sample (at the time of entry) with a polynomial of order 3, and for the probability of remaining in the sample (for those who stayed) with another polynomial of order 3. Each model also include control variables for which we do not report the effect: education, weather (rain volume and average temperature in winter and summer), sectoral composition of the local firms, local number of households and share of retired households. Rents and housing-type availability have an effect only on the concerned housing type subsample (private rents affect both private and precarious renters), except for the stock of private renters from the CAF, which is a measure of local poverty and could affect every households. We do not report the homeowner and unstable subsample results.

5 Conclusion

This paper provides new evidence on extreme poverty in an advanced market economy, using a novel administrative dataset from France's largest food assistance charity covering over 5 million unique individuals between 2017 and 2025.

Our first set of findings concerns the exposure of the poor to aggregate economic conditions. Local macroeconomic forces, including unemployment, private housing rents, food prices, and firm dynamism, are powerful drivers of entry into homelessness and food insecurity, while the same forces are largely irrelevant for exits. The key determinant of exit is instead the duration of the poverty spell itself. This asymmetry means aggregate conditions push people into extreme poverty far more effectively than they pull them back out.

Our second set of findings concerns how poor households allocate their resources. We document a striking pattern in their Engel curves: housing behaves as a luxury good even at very low income levels, with households allocating virtually all marginal income to non-housing needs below a subsistence threshold of roughly 400€ per consumption unit per month, and a marginal propensity to consume housing of around 0.5 above it. The rest for living is remarkably stable across housing situations at around 350€ per person per month, suggesting that basic necessities are on average satisfied at this threshold, beyond which additional income flows almost entirely into housing.

Prevention is therefore where policy has the most leverage, through labor market stability, affordable housing supply, and price stability. For those who have already fallen in, aggregate conditions are of little help; what matters is early, targeted support, deployed before duration dependence makes escape increasingly hard.

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A Accuracy and Representativeness of RDC Data

In this section we discuss the extent to which our data is a selected sample of the poor living in France. To do so, we compare it to available survey data (HFCS and EU-SILC) and, for French residents, to the CAF data described above. We focus both on the overall RDC sample and on the homeless in particular. We end by briefly discussing the reporting accuracy of our data.

Overall RDC Recipients: Comparison with Survey Data. Figure **??** depicts the distributions of income per CU (right panel) and rest for living (normalized by the household-specific threshold of eligibility into RDC, left panel) in our sample of French residents, for both homeless and non-homeless recipients. The income distributions show clear bunching masses corresponding to the levels of the RSA transfer for individuals and couples without children. Table 9 complements these figures by reporting moments of the income distribution and demographic characteristics in the RDC sample and in the HFCS and EU-SILC survey panels for France. Notice first that, in comparison to these surveys, our data set contains individuals with relatively high monthly incomes (including transfers). The 90^{th} percentile in our sample (excluding non-residents) is at 1,300€, and the 97.5^{th} percentile is slightly above 1,700€. By comparison, the HFCS places the 10^{th} percentile of the overall French income distribution at 1,100€, while the 25^{th} percentile is around 1,640€.[60] In other words, the highest income in RDC is at a similar level as the 25^{th} percentile in the HFCS; 80% of the RDC recipients have income below the 10^{th} percentile; and only 50% are located below the 5^{th} percentile. The comparison with EU-SILC is broadly similar.[61]

Given that our sample (including non-residents) contains less than 2% of the French population, these comparisons suggest either that our sample misses a very large share of the income-poor, or that survey data are severely mismeasuring the bottom tail. The latter is the most likely explanation: the bottom tail in surveys, just like the top tail, seems to be plagued by severe misrepresentation and misreporting. For instance, Table 9 shows that both surveys have an excessively large fraction of homeowners (about 25% in the bottom 10% for HFCS, 35% in the EU-SILC, compared to 4.7% in our sample). Relatedly, there are major age differences between the surveys and RDC: the average age in the bottom 10% earners in EU-SILC is 57 years old (51 in HFCS), vs. 46 in RDC (or 42 if we include

[60] An income of $1,500$ is often reported as being the threshold of the bottom 10% of the distribution (see, e.g., Observatoire des inégalités).

[61] Comparing our sample to EU-SILC suggests that 85% of the sample falls below the 10^{th} percentile, and about 60% lies below the 5^{th} percentile.

non-residents). This probably reflects that sampling issues may be particularly severe for younger households. Most importantly, the HFCS and EU-SILC severely understate the take-up of welfare benefits by French residents. The misreporting of transfers is a major problem that is common to surveys in general, and that has become more pronounced in the past few years; see, e.g., Meyer et al. (2015).[62] We find that the HFCS and EU-SILC cover a small fraction of the transfers relative to the total distributed amounts recorded in the administrative CAF data: between 40% and 45% overall, 25-30% of the unemployment benefits, 42% for family allowance, 79% for housing allowance, and 66% for social assistance benefits. This is due to an under-reporting both on the extensive and the intensive margins: in HFCS, 57.1% of individuals in the bottom 10% report receiving transfers, vs. 85% in our sample, and the mean transfer conditional on take-up is 281€ vs. 634€ in RDC. In EU-SILC, the transfer take-up is substantially higher (93.8% of households in the bottom 10% receive transfers) but the average amount (348€) remains below that in RdC. Overall, this means that incomes in the left tail are in reality significantly larger than such surveys would suggest. In fact, as we saw in Table 1, welfare transfers are by far the largest income source for RDC recipients. Finally, the surveys also overestimate the share of indebted individuals (18% vs 12.5% in our sample).

Lastly, to the extent that survey data do contain a significant number of observations with incomes lower than most RDC recipients, one should not conclude that our data set misses a large fraction of the poor in France. Specifically, individuals in our sample should not be interpreted as necessarily the most *income*-poor in France. Rather, they are the *consumption*-poor, which we think is a more relevant measure of poverty; by definition, they are those who face severe deprivation and request food assistance. For instance, even if survey data suggest that their income would place them close to the second decile of the overall French distribution, an individual with 1,300€ of income (including transfers) might be in extreme poverty, to the point of requesting help from RDC, if they live in Paris where rents are particularly high, or if they lack a support network that can provide insurance against economic hardships.

Homeless RDC Recipients: Comparison with Survey and OECD Data. As most household surveys, neither EU-SILC nor the HFCS can capture people currently experiencing homelessness in France, because both surveys sample only private households living in an ordinary main residence.[63] As a result, extreme poverty and housing exclusion are sys-

[62] For instance, in the U.S. less than 60% of SNAP receipts were reported in the CPS c. 2010.

[63] See here and here for the sampling restrictions of EU-SILC and here for those of the HFCS.

tematically under-represented in both datasets; only homeless individuals temporarily living with friends or family (which are part of our "broad" definition of housing instability) may appear as part of a surveyed household. Starting in 2019, however, EU-SILC added limited retrospective questions on past experiences of homelessness or severe housing precarity (note that currently homeless individuals remain outside of the core sampling frame).[64] In this sample, 143 individuals report having slept rough at some point in their lives, and only 12 report having done so within the last five years. When weighted, this corresponds to roughly 32,000 individuals, or around 0.06% of the French population. By comparison, recall that in the RDC data, roughly 0.67% of the French population are experiencing (broad) homelessness in each wave of our sample, and 2.9% of the population experienced homelessness in the past 7 years – multiple orders of magnitude more than the survey suggests.

To our knowledge, the most comprehensive and reliable outside estimate of the overall number of homeless individuals in France is that measured by the OECD.[65] They confronted multiple reliable sources to estimate that France counted 333,000 homeless individuals in 2022, representing 0.49% of the total population. Their definition of homelessness includes people sleeping in a place not intended for habitation or in an accommodation without rental contract (including refugee shelters), but ignores individuals living in other unstable conditions (e.g., hosted by third parties, etc.). Using a similar definition, our data in 2022 yields a rate of homelessness of 0.41% on average across the two waves of the survey, or about 84% of that estimated by the OECD.[66,67] Including precarious and inadequate housing conditions, which we also observe in our data, further raises this population share to 0.61% or 124% of the OECD count, significantly more than estimated by the OECD. These results

[64]Specifically, a new question introduced in 2023 asks respondents whether they have ever faced housing difficulties that forced them to live temporarily with friends or relatives, stayed in emergency or other temporary accommodation, resided in a place not intended as a permanent home, or slept rough in public space. See here.

[65]Source: click here.

[66]More precisely, there are 210,005 (resp., 335,790) individuals who report being either homeless or in shelters (resp., in other unstable situations) in the 2022 winter wave, and 228,647 (resp., 368,616) in the summer wave. Among the non-responses to the housing question, a fraction (around 25% for the French residents and 90% for the non-residents) of applicants also report having 0 housing expenses. We include these observations into homelessness, thus raising the total count by an additional 39,453 individuals in the winter, and 75,128 individuals in the summer.

[67]The similarity of our estimate and that of the OECD might hide composition effects. First, one of the sources used by the OECD (the INSEE homelessness survey, which dates back to 2012), focuses on cities with more than 20,000 inhabitants, with some information about cities with more than 5,000 inhabitants. Since we also observe homeless individuals in smaller towns, it is possible that we under-estimate the number of homeless in bigger cities by an equivalent amount. Second, the OECD defines homelessness as having been unhoused "the previous night". Our bi-annual survey might miss households facing such transitory shocks and capture more permanent situations.

are reported in the right panel of Figure 1, which also gives the homelessness rates of all other OECD countries.[68] This comparison suggests that our sample contains a very large share of the homeless population, and more generally of the households in unstable housing situations, in France.

Nevertheless, one might worry that RDC's eligibility criterion mechanically restricts the number of homeless individuals in our sample. Because they have much lower housing expenditures than tenants, it is possible that their rest for living (income minus housing expenses) ends up relatively higher, thus placing them at risk of being rejected by the charity. This does not seem to be a major concern in practice: it appears that the homeless in our sample are mostly infra-marginal recipients, and hence likely to be systematically accepted into RDC. First, Figure 16 gives the breakdown of recipients by housing status in our sample. It shows that up until 2023, the share of unstable (i.e., broadly homeless) recipients exhibits a strong seasonal pattern: it is smaller in the winter than in the summer wave, a pattern that mirrors that of social housing tenants. Recall that until 2023, RDC's eligibility threshold was more generous in the winter, leading to a correspondingly larger number of recipients. Thus, the seasonality pattern of enrollments is highly suggestive that the marginal recipients are social housing tenants, while the homeless are inframarginal. Second, Figure 17 shows that the rest for living of homeless recipients, even among the French residents, is indeed systematically lower than that of other households. Including the non-residents further reinforces this finding, as shown in Figure 18. The right panels of these figures show that this is caused in large part by the fact that they have far smaller incomes than the rest of the population. In particular, a much larger share of homeless individuals report receiving zero income than the rest of the sample. This is due to the combination of several factors: (i) the homeless are much younger on average (see Table 1), which means that they are less likely to receive both the RSA transfer (if they are younger than 25) and pensions – these are the two largest sources of income in our sample; (ii) their salaries are lower, conditional on working; (iii) their take-up of welfare benefits is lower. Finally, Figure 19 shows that, controlling for individual characteristics, the homeless are more likely to get accepted than other applicants when they are located to the right of RDC's eligibility threshold. Overall, about 94% of the homeless in our sample get accepted to receive food assistance, vs. 89.5% for other housing types.[69]

[68] Note that different methodologies make the comparison between countries difficult. For instance, in contrast to France, New Zealand includes all unstable housing situations in their definition of homelessness.

[69] Recall that we also observe the characteristics of those who applied but did not get accepted.

Reporting Accuracy. Applicants may have incentives to under-report income or over-report expenses in order to clear the eligibility threshold. This issue is partly alleviated by the fact that they must, to the extent possible, provide verifiable evidence of their income and expenses every time they apply to renew their enrollment. For instance, if they report earning a certain level of income that allows them to be eligible to some government transfers, they must show proof that they are indeed receiving these transfers. Such a verification is more difficult for non-residents, e.g. undocumented immigrants who are not eligible to receive any transfers.

One (imperfect) way to test whether there is indeed misreporting is to plot the distribution of rest for living and check whether there is an unexpected bunching mass at the eligibility threshold. Figure 20 shows the results for the summer and winter 2021. The eligibility threshold is normalized at 0 on the horizontal axis. In both waves, we do observe a clear bunching mass at the threshold. This could be due to several reasons. First, applicants may misreport their true economic situation. Second, volunteers who run the survey may alter the true values when entering an applicant's information in the database (even though being slightly above the eligibility threshold could still allow an individual to receive assistance if the volunteers collectively decide so, see Figure 2). Third, there might be self-selection, whereby individuals who know that they are not eligible for assistance choose not to apply. The bottom right panel shows another bunching mass at the *previous* wave's eligibility threshold, suggesting some learning by applicants. This is consistent with the self-selection explanation, especially if the fixed cost associated with filling out the questionnaire giving access to food assistance is perceived as substantial for the marginal individuals.

B Additional Figures

Figure 15. Price level across département.

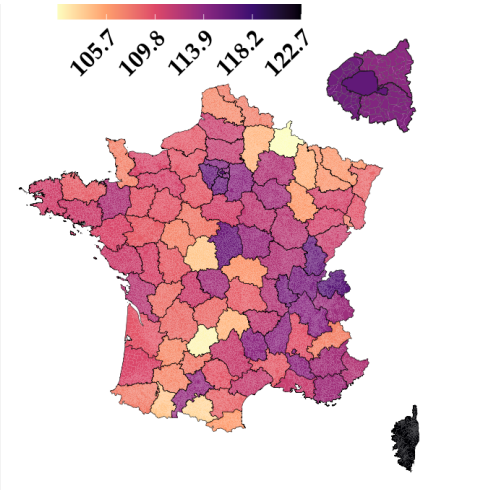


Figure 16. Housing Status Over Time.

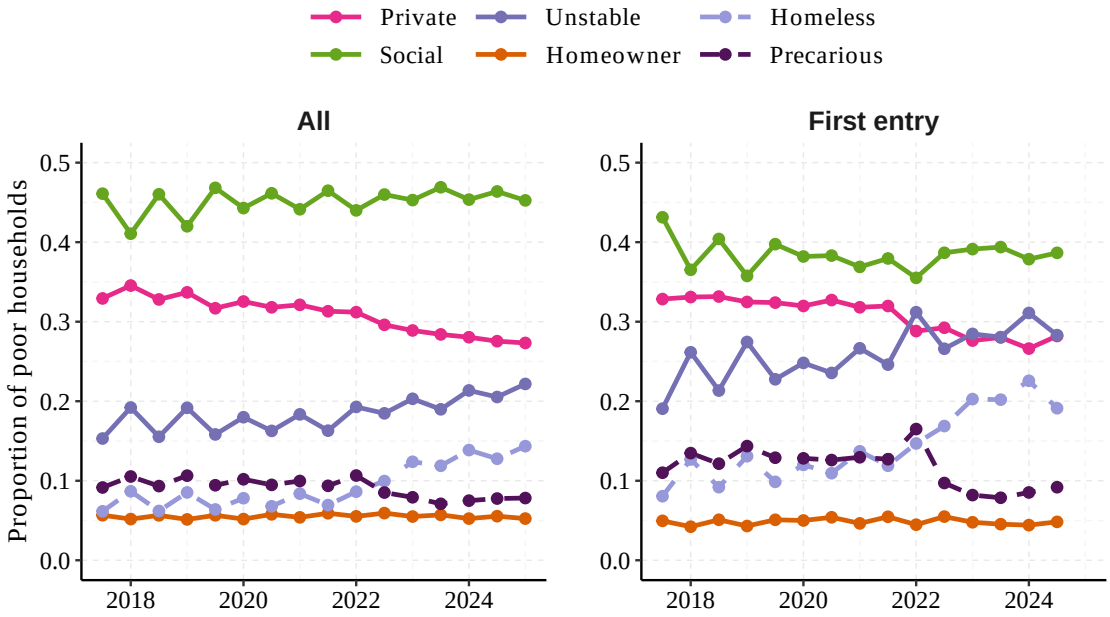


Figure 17. Relative densities of housed and homeless individuals among French residents

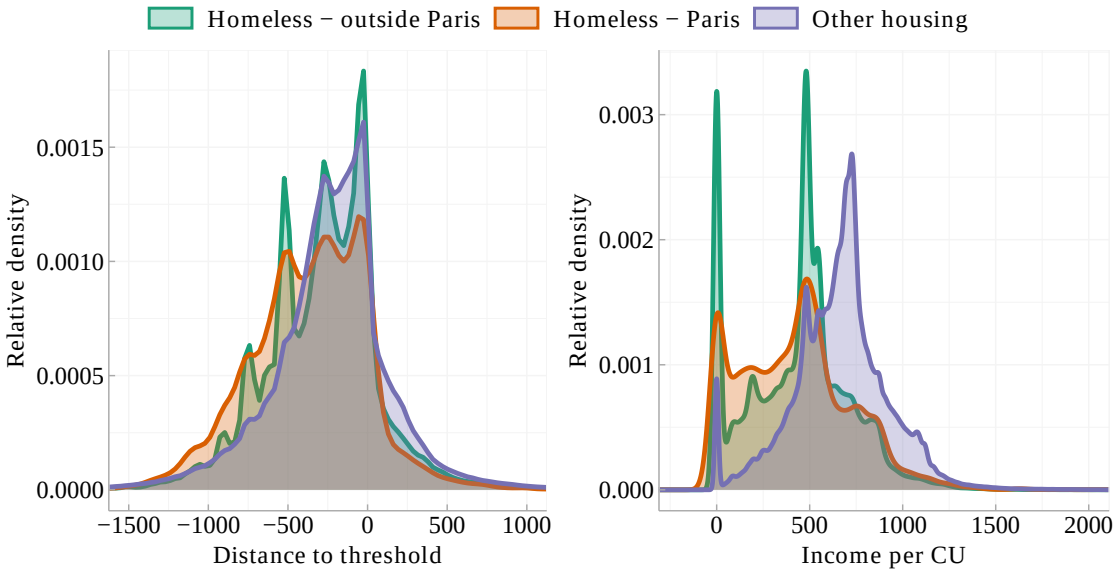


Figure 18. Relative densities of housed and homeless individuals among all recipients

Table 9. Comparison Across EU-SILC, HFCS, and RdC Samples

Income distribution	p05	p10	p25	p50	p75	p90
EU-SILC (2022)	973	1240	1851	2845	4397	6242
EU-SILC (2022), bottom 10%	48	373	738	973	1138	1203
RdC 2022	141	400	641	847	1136	1417
RdC 2022 (with non-resident)	0	0	0	520	920	1242
HFCS (2020)	733	1088	1638	2621	4169	6158
HFCS (2020), bottom 10%	0	4.5	300	733	951	1043
RdC 2020	166	408	629	790	1075	1325
RdC 2020 (with non-resident)	0	0	100	599	909	1202

Demographic characteristics	Age	HH size	% of the population homeowners	% of the population in debt	With transfer	Mean transfer
EU-SILC (2022)	54.7	2.17	0.610	–	0.769	266
EU-SILC (2022), bottom 10%	57.4	1.25	0.351	–	0.938	348
RdC 2022	46.4	2.26	0.049	0.147	0.828	614
RdC 2022 (with non-resident)	41.9	2.25	0.028	0.085	0.465	345
HFCS (2020)	54.3	2.16	0.575	0.438	0.471	285
HFCS (2020), bottom 10%	50.8	1.37	0.285	0.176	0.571	281
RdC	46.1	2.23	0.047	0.125	0.853	634
RdC (with non-resident)	42.1	2.28	0.030	0.078	0.525	391

Figure 19. Probability of acceptance by housing situation (before 2024)

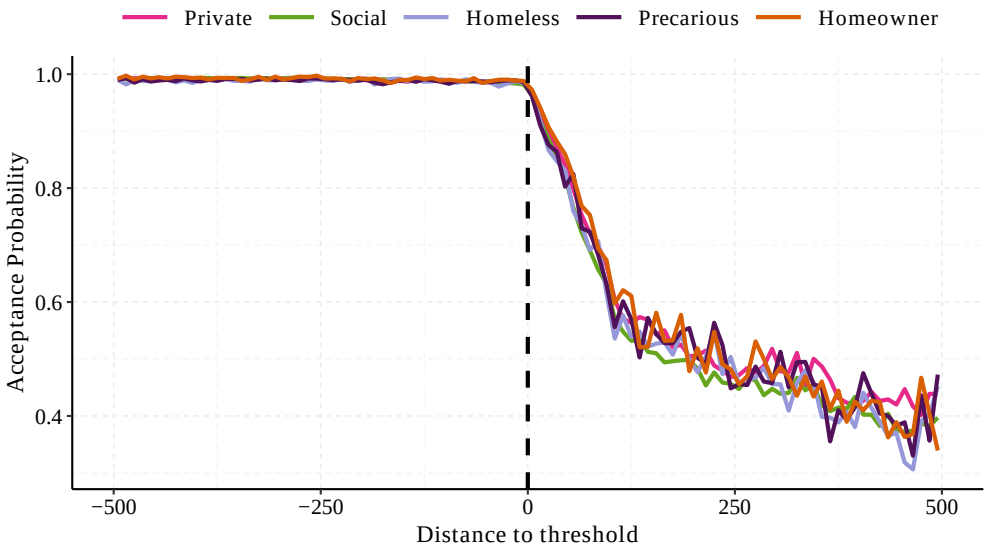
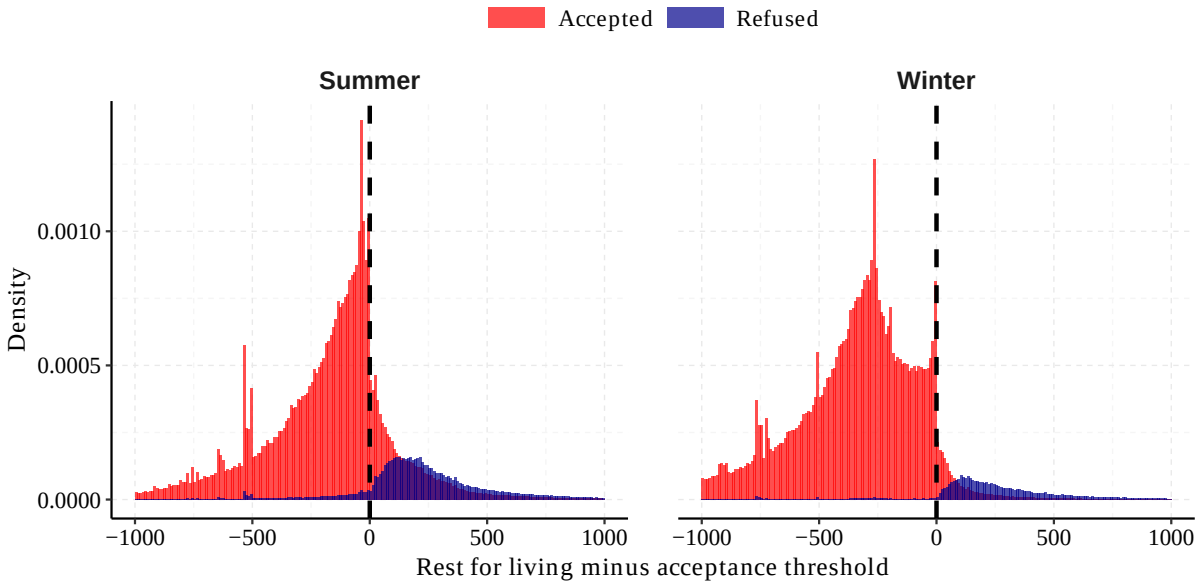


Figure 20. Distribution of rest for living, normalized by household-specific eligibility threshold.

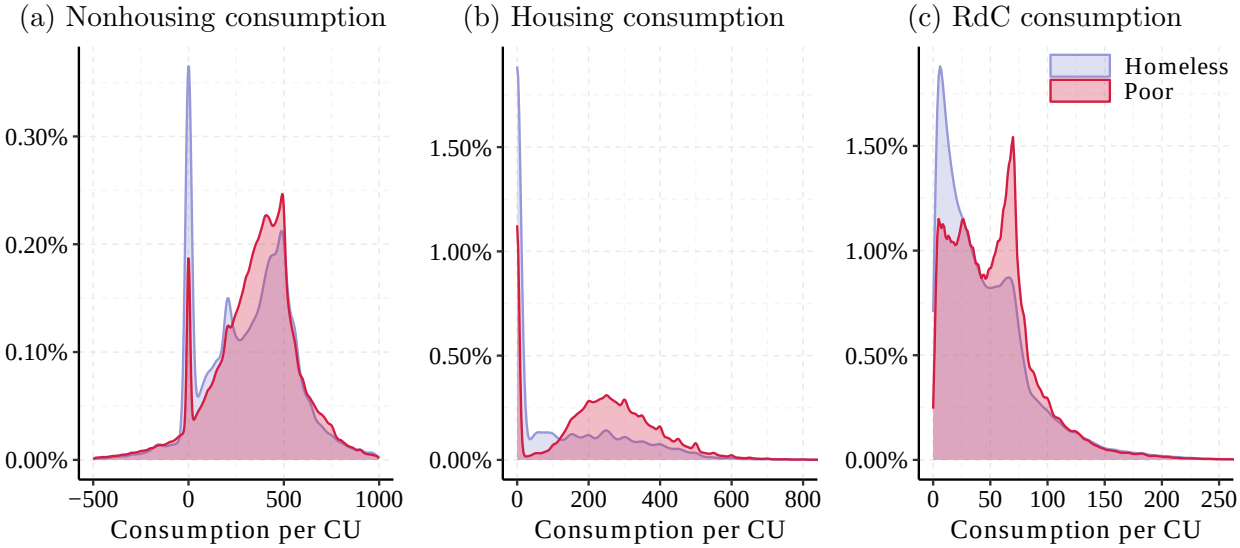


C Additional Results

C.1 Finances of the Residents

C.1.1 Consumption patterns

Figure 21. Distributions of consumption per CU.



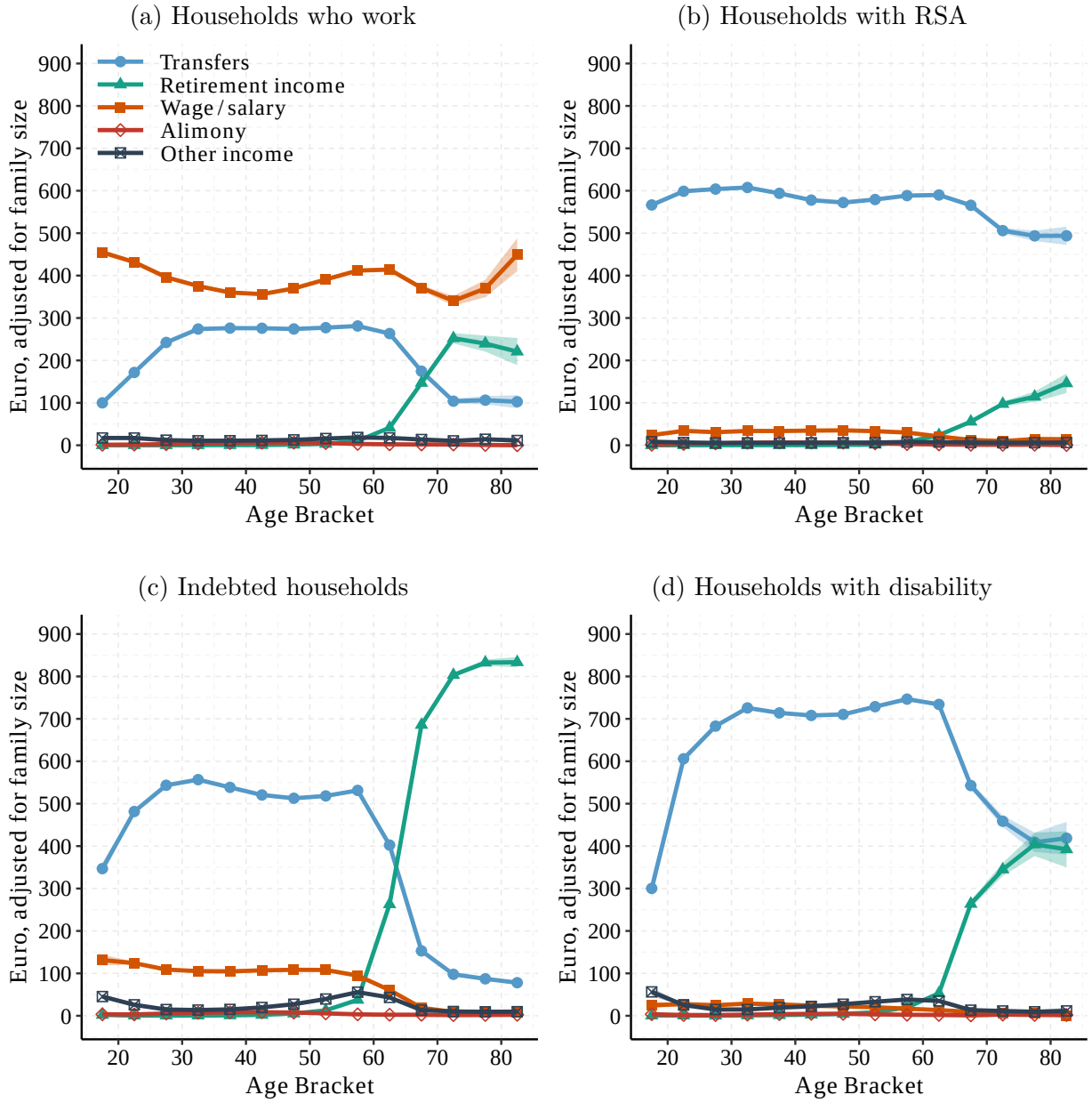
C.1.2 Conditional Finances

C.1.3 Zero-Income Residents and Take-Up of Transfers

In our sample of residents, individuals with no income are either those who are not yet eligible to receive the RSA, e.g. students younger than the minimum age requirement (typically 25 years old), or those who have applied to the RSA allowance but not yet received a transfer. Figures 26 and 27 compare compare this group with those with higher incomes along several dimensions: age, family structure, occupation, citizenship, and duration at RDC. These recipients are much more likely to be younger than age 25, single without children, students and/or not employed, French, and they are overwhelmingly first-time entrants into RDC.

Given the importance of government transfers in residents' finances, we conclude by briefly discussing how likely RDC recipients are to take up the welfare benefits to which they are eligible, and what are possible reasons for such incomplete take-up. Among French citizens above the age of 25, XX% report having no income (and hence no transfers), even

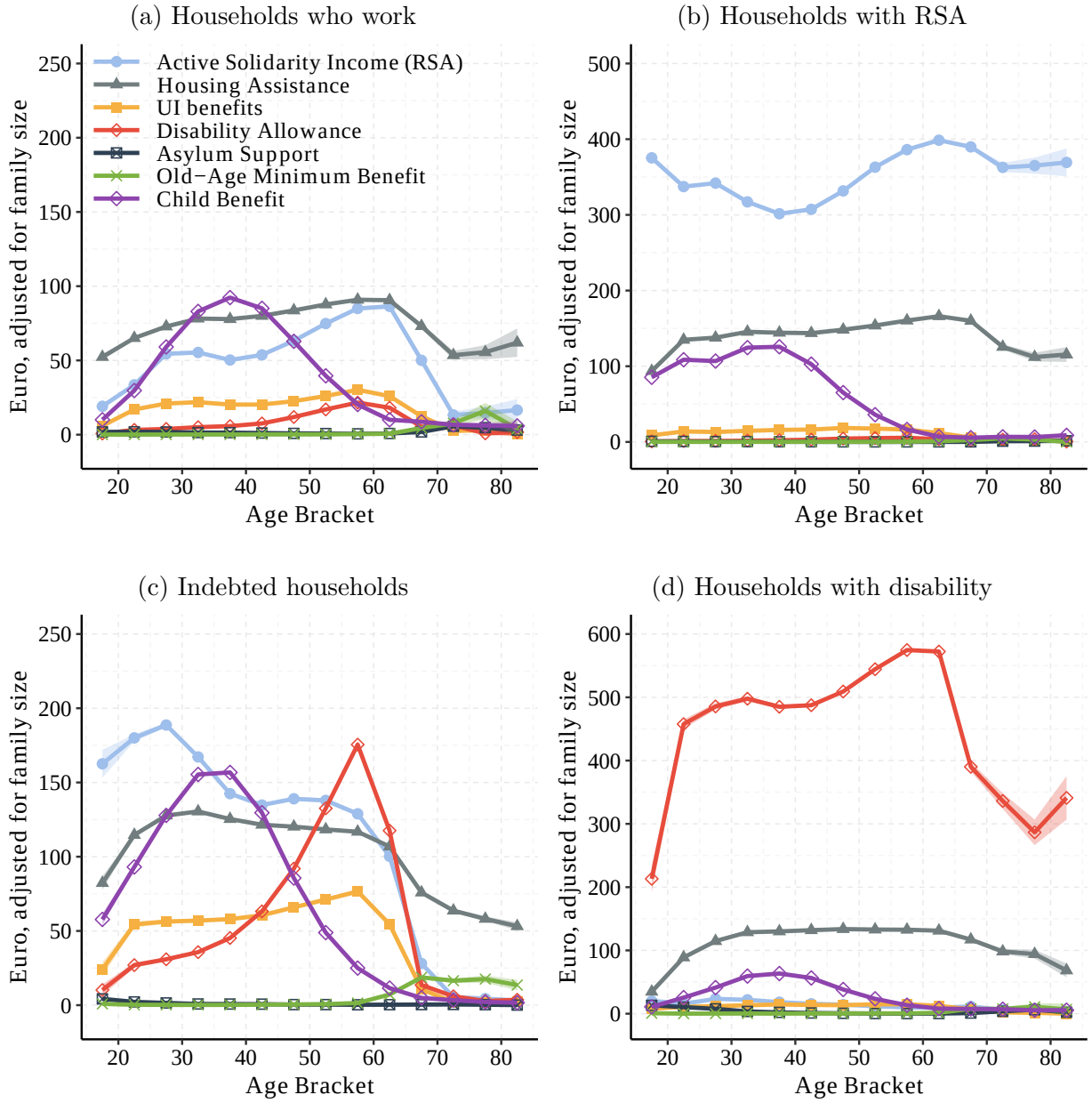
Figure 22. Conditional decomposition of average income over the life cycle for selected subsamples



though they could in theory receive the maximum RSA allowance.[70] Among the homeless, this proportion rises to XX%. To better understand the factors that correlate with incomplete take-up, we use the complementary survey run by RDC in 2025. To the question "Do you have difficulties accessing your entitlements (social assistance, housing subsidies, administrative procedures, etc.)", 50% respond "No difficulty", 28% respond "Some difficulty",

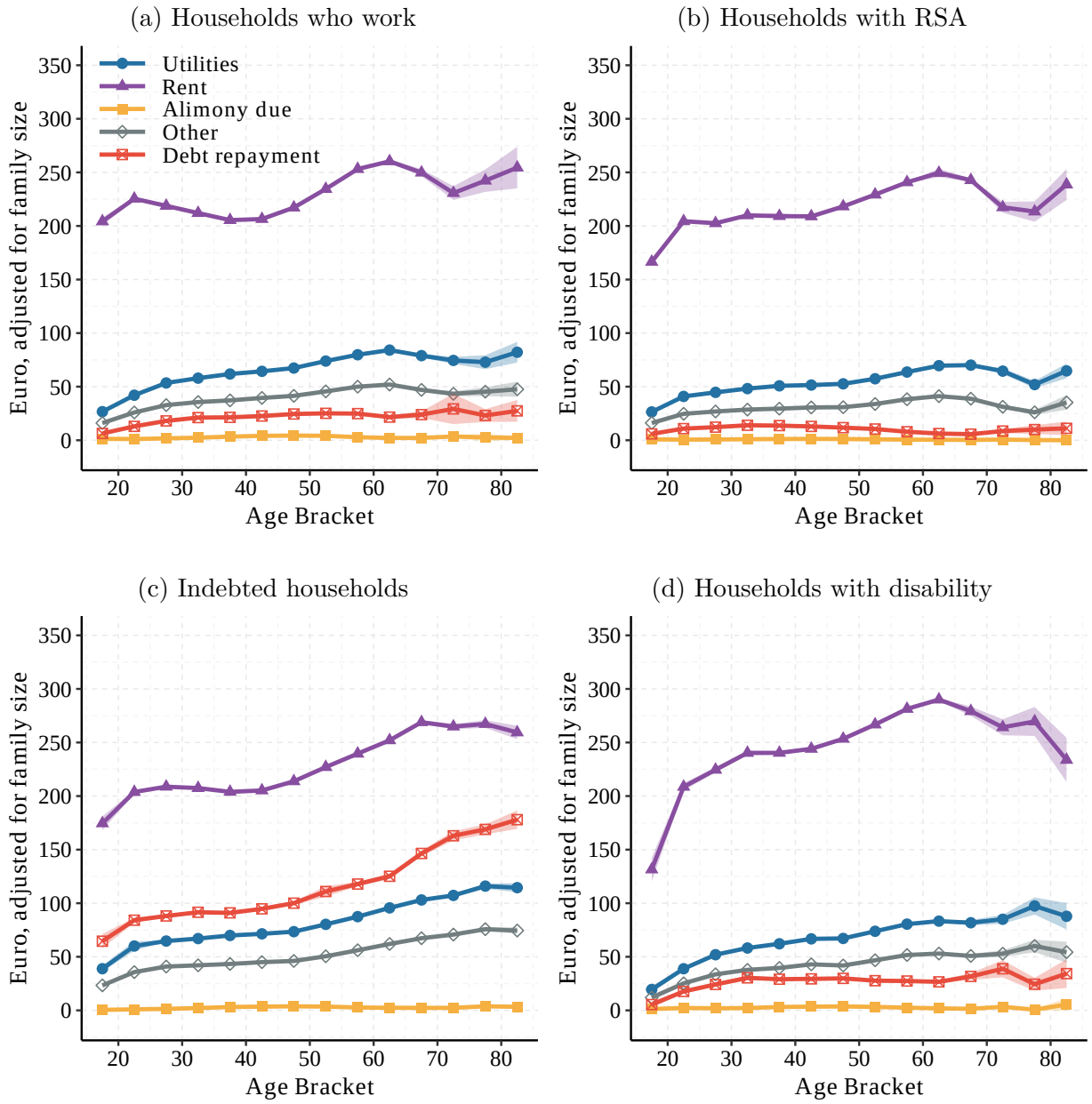
[70]These values might be larger than for poor households who use other charities that may not request proof of resources to access their services.

Figure 23. Conditional decomposition of average transfers over the life cycle for selected subsamples



and 12% respond "Significant difficulty". Figure 28 shows that recipients who find it more difficult to take up benefits are significantly more likely to lack computer access and to be experiencing periods of emotional hardship. Focusing on individuals in unstable housing situations, the left panel of Figure 29 shows that about 26% (resp., 28%) of them find it very difficult (resp., somewhat difficult) to take up benefits – a much larger share than among private or social housing tenants. They are also more likely to report that they are aware that their situation can improve but don't know how to get help or cannot bring themselves

Figure 24. Conditional decomposition of average expenses over the life cycle for selected subsamples



to do it.

C.1.4 Migration patterns

Table 10 shows the migration patterns for residents and non-resident French households.

Figure 25. Median income (left), expenses (middle), and rest for living (right) by housing situation (French residents).

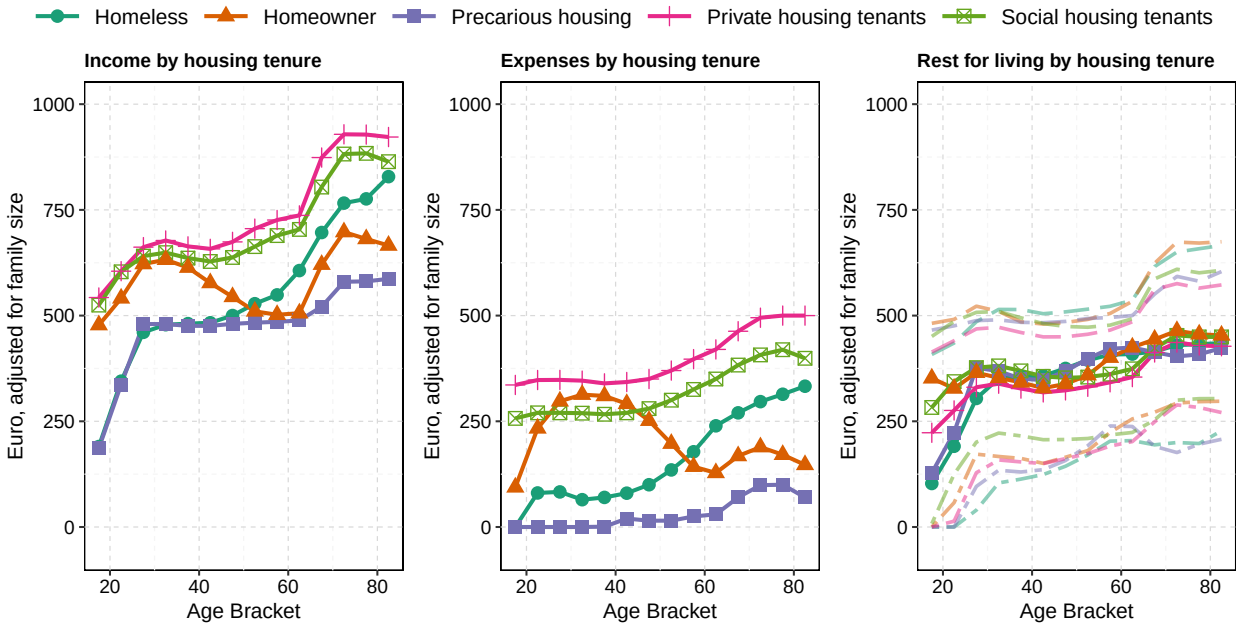


Table 10. Share of families who moved across geographical units, by housing tenure and residency status

	Residents			Non-residents		
Housing type	Département	EPCI	Commune	Département	EPCI	Commune
All	0.066	0.382	1.202	0.073	0.346	1.986
Homeowner	0.032	0.165	0.383	0.048	0.048	0.145
Social housing	0.016	0.115	0.485	0.036	0.151	0.859
Homeless/Precarious	0.117	0.602	2.010	0.073	0.359	2.066
Private renters	0.080	0.442	1.199	0.061	0.168	0.935

Figure 26. Zero income group: age (top left), family structure (top right), occupation (bottom left), and citizenship (bottom right)

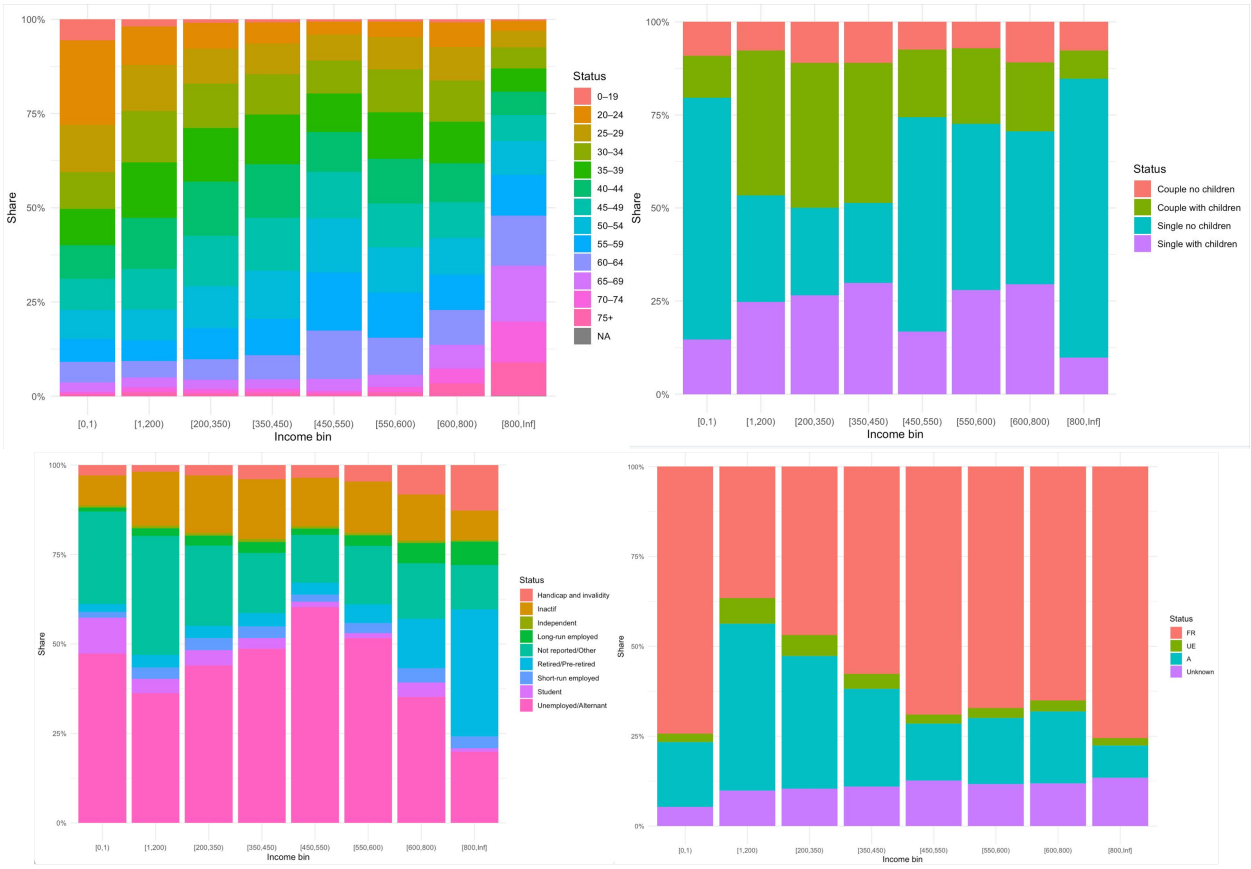


Figure 27. Zero income group: duration in RDC

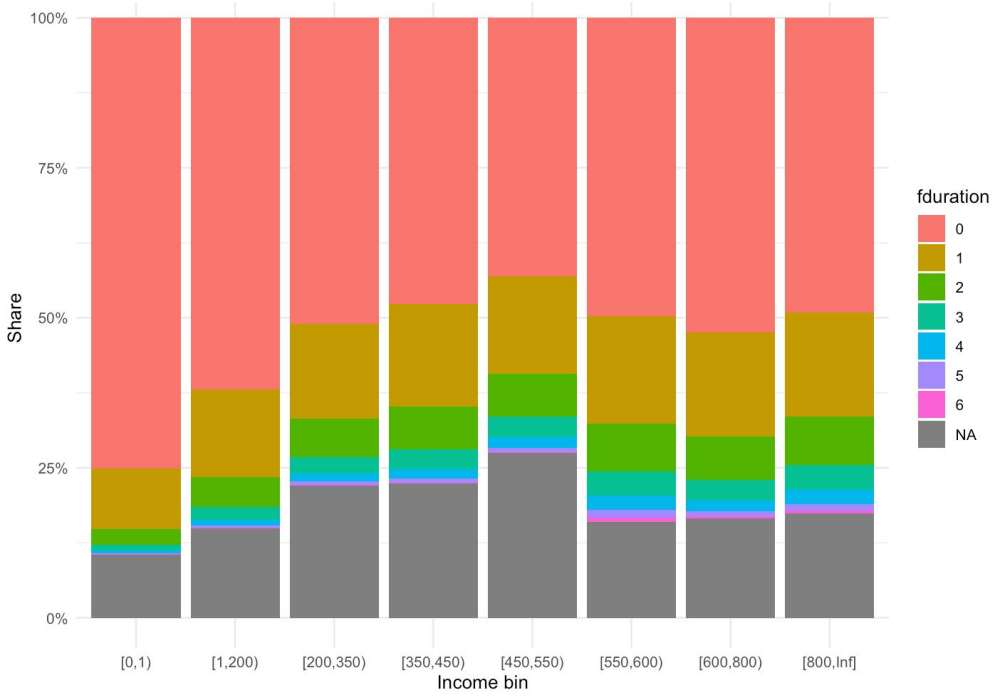


Figure 28. Welfare benefit take-up: roles of technology access and mental health.

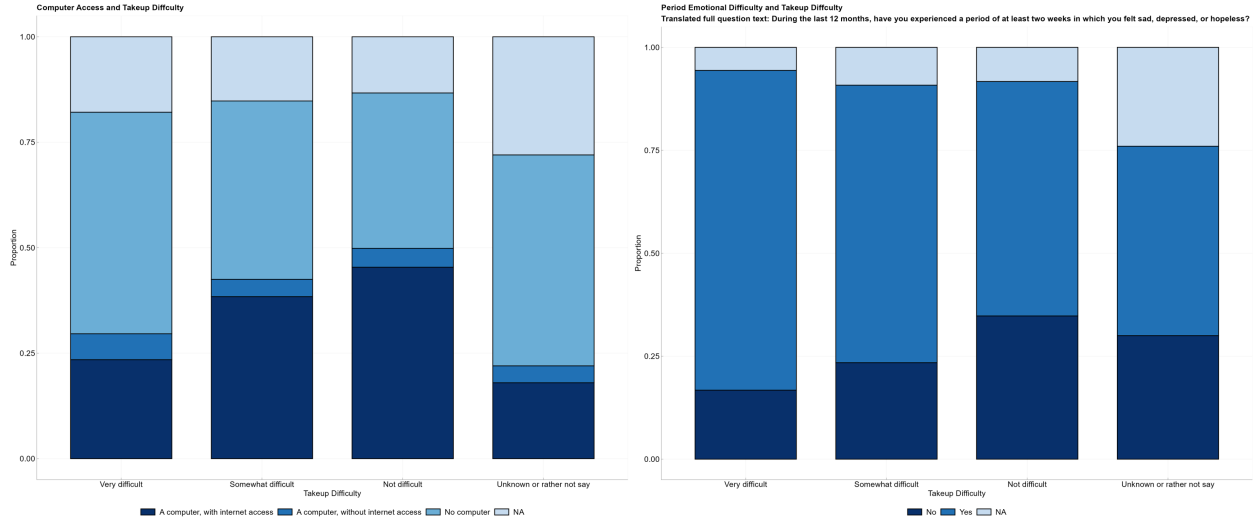
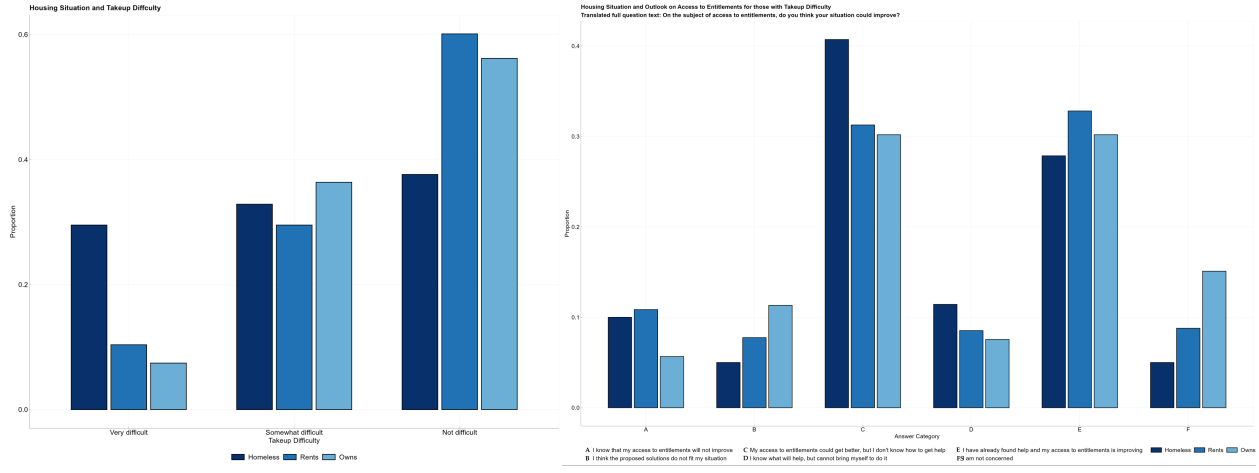


Figure 29. Welfare benefit take-up difficulty and expectations of improvement by housing status.



Note: The right panel is restricted to respondents who find it "somewhat difficult" or "very difficult" to take up welfare benefits.

C.2 The Non-Residents

Summary statistics. Table 1 reports summary statistics for non-resident French households in the RDC sample, overall and by housing status. The population is relatively young (average age 36) and mostly single. Family sizes are small, with fewer than one child on average. Labor market attachment is extremely limited, with very low employment rates and almost no retirees, consistent with a population largely excluded from standard labor market and pension systems.

Financially, non-resident households have very low income, less than €per month. As a result, resources left for consumption are often limited or even negative in private housing. Compared to France-wide averages, non-residents are concentrated in poorer local environments, with higher unemployment, higher rents, and greater exposure to dense urban areas.

C.3 Non-resident and Resident disparities

Spatial disparities. Figure 30 compares the spatial distribution of poor and homeless populations across residents and non-residents. While both groups exhibit substantial geographic heterogeneity, non-resident populations are more unevenly distributed and tend to be more concentrated in specific areas. The patterns are broadly similar across poor and homeless populations.

Distributions of age and income. Figure 31 reports the distributions of age and income for non-resident French households. The age distribution is skewed toward younger and middle-age individuals, with fewer older households compared to the general population. Income distributions are highly concentrated at low levels, with a large mass near zero, even when excluding housing benefits. This highlights the limited access of non-resident households to stable income sources.

C.4 Finances of the Non-Residents

C.4.1 Consumption patterns

C.4.2 Life Cycle patterns

Figure 33 shows the evolution of average income and transfers over the life cycle. Income remains extremely low at all ages. Transfers (asylum support) and other income play a

Table 11. Summary statistics for non French residents: full sample and by housing status.

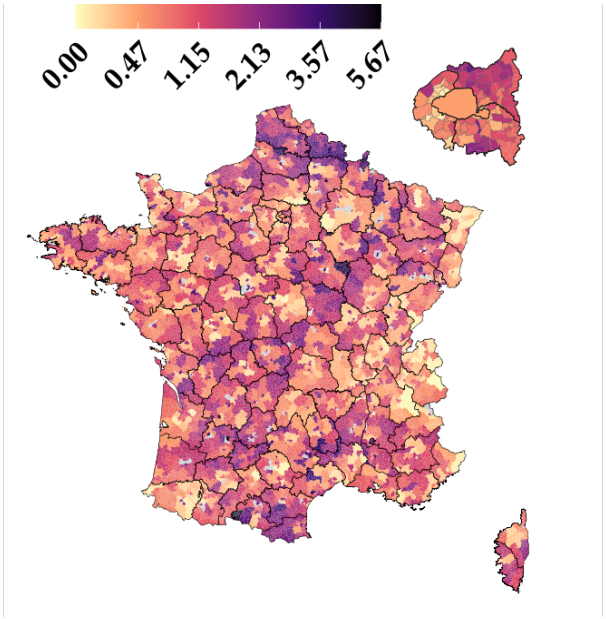
	RDC Sample								France°
	Full Sample		Private Rental		Social Housing		Unstable Housing		
Variable	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean
Demographics									
Age	35.63	(12.30)	34.16	(12.58)	36.08	(13.40)	35.79	(12.09)	54.7
Family consumption units	1.48	(0.603)	1.53	(0.663)	1.47	(0.644)	1.48	(0.591)	1.51
Couple	0.310	(0.463)	0.373	(0.484)	0.275	(0.446)	0.310	(0.462)	0.590
Single man	0.329	(0.470)	0.287	(0.452)	0.346	(0.476)	0.323	(0.468)	
Single woman	0.361	(0.480)	0.340	(0.474)	0.380	(0.485)	0.367	(0.482)	
# children	0.873	(1.21)	0.883	(1.27)	0.839	(1.30)	0.894	(1.20)	1.035
# children aged 0–3	0.254	(0.514)	0.179	(0.436)	0.185	(0.450)	0.275	(0.528)	
# children aged 4–12	0.468	(0.863)	0.529	(0.911)	0.479	(0.902)	0.474	(0.853)	
# children aged 13+	0.151	(0.453)	0.174	(0.477)	0.175	(0.499)	0.145	(0.439)	
Student	0.087	(0.282)	0.357	(0.479)	0.174	(0.379)	0.052	(0.222)	0.050
Retired / pre-retired	0.006	(0.080)	0.010	(0.101)	0.018	(0.134)	0.005	(0.069)	0.283
Finances (per CU)									
Work	0.020	(0.141)	0.037	(0.189)	0.046	(0.210)	0.011	(0.105)	0.530
Earnings	0.303	(10.47)	0.818	(17.72)	1.51	(21.64)	0.163	(7.92)	
Total income	122.51	(178.34)	255.53	(284.75)	217.68	(252.73)	105.74	(146.11)	2256.98
Transfers	27.68	(80.33)	11.76	(63.06)	53.06	(105.91)	30.20	(82.62)	188.74
Expenses	44.42	(135.05)	268.56	(197.82)	133.57	(287.37)	16.06	(70.84)	
Housing expenses	34.57	(103.11)	220.19	(180.61)	88.39	(145.11)	13.26	(62.81)	326.56
Resources left for consumption	78.09	(172.47)	-13.03	(265.76)	84.11	(320.76)	89.68	(138.07)	
Consumption according to RDC	46.91	(42.32)	42.71	(39.79)	43.55	(39.12)	48.95	(43.23)	
In debt	0.016	(0.127)	0.026	(0.159)	0.045	(0.207)	0.014	(0.116)	0.438
Debt conditional on being in debt	46.16	(465.05)	98.67	(289.11)	118.27	(1035.21)	13.37	(89.84)	
Survival in sample									
Goes to the charity next year	0.427	(0.495)	0.429	(0.495)	0.395	(0.489)	0.447	(0.497)	
Local covariates (canton level)									
Avg annual income (in k€)	16.13	(4.77)	15.27	(4.21)	15.96	(4.17)	16.35	(5.00)	17.13
Unemployment (broad) rate (%)	20.55	5.04	21.83	5.52	19.67	4.77	20.41	5.01	18.28
Private rent (€/sqm)	15.86	(6.17)	15.41	(5.49)	14.53	(5.70)	16.26	(6.37)	14.08
Private rent (CAF, €/sqm)	11.29	(3.50)	10.88	(3.24)	10.25	(3.25)	11.53	(3.59)	10.38
Social rent (€/sqm)	5.96	(0.863)	5.92	(0.817)	5.83	(0.861)	6.02	(0.877)	5.77
Private rentals per k hh	96.92	(60.41)	97.18	(59.59)	85.42	(55.80)	96.40	(60.16)	66.31
Social housing units per k hh	188.93	(81.24)	186.35	(85.14)	177.18	(86.67)	192.07	(80.04)	129.87
Shelter capacity per k hh	13.13	(8.97)	12.50	(9.35)	11.33	(9.56)	13.56	(8.90)	7.17
Price index	111.96	(9.63)	112.79	(9.91)	115.38	(9.63)	112.35	(9.71)	109.35
Firm stock (per k hh)	147.43	(51.51)	141.80	(45.09)	141.28	(46.27)	148.75	(53.41)	142.12
Urbanization									
City center	0.594	(0.491)	0.620	(0.485)	0.581	(0.493)	0.588	(0.492)	0.317
Suburb	0.339	(0.474)	0.303	(0.460)	0.294	(0.456)	0.355	(0.479)	0.379
Isolated city	0.050	(0.218)	0.050	(0.218)	0.099	(0.299)	0.043	(0.203)	0.090
Rural area	0.017	(0.129)	0.027	(0.163)	0.026	(0.159)	0.013	(0.113)	0.214
Share of observations	100%		8.50%		7.70%		83.80%		

° *Notes:* Overall France values are (i) gathered from outside source for individual information (age, couple, etc.). For local covariates, we report the canton averages or postal code averages (for urbanization), weighted by population, between 2018 and 2023.

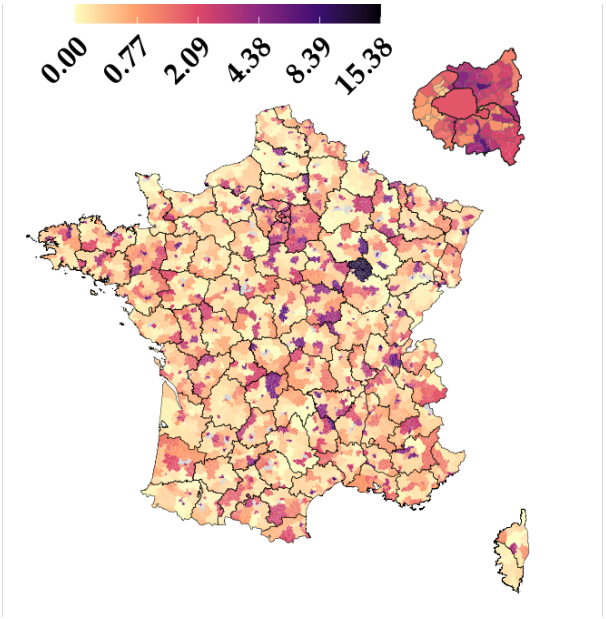
central role and constitute the primary source of resources. Figure 34 presents the evolution of expenses and consumption. Housing-related expenses are limited at all ages. RdC food provision is of a magnitude comparable to households' remaining rest for living, suggesting that access to the charity is vital for non resident French.

Figure 30. Dispersion of poor/homeless per 1,000 households relative to the sub-sample mean, for residents and non-residents.

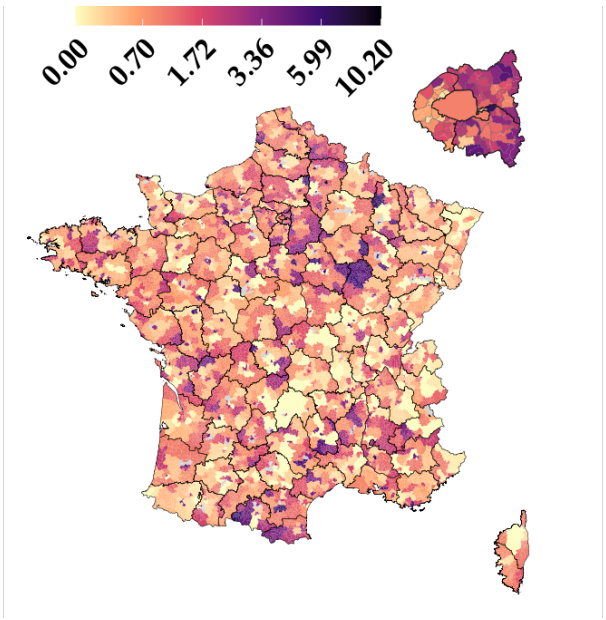
(a) Resident (Poor)



(b) Non-resident (Poor)



(c) Resident (Homeless)



(d) Non-resident (Homeless)

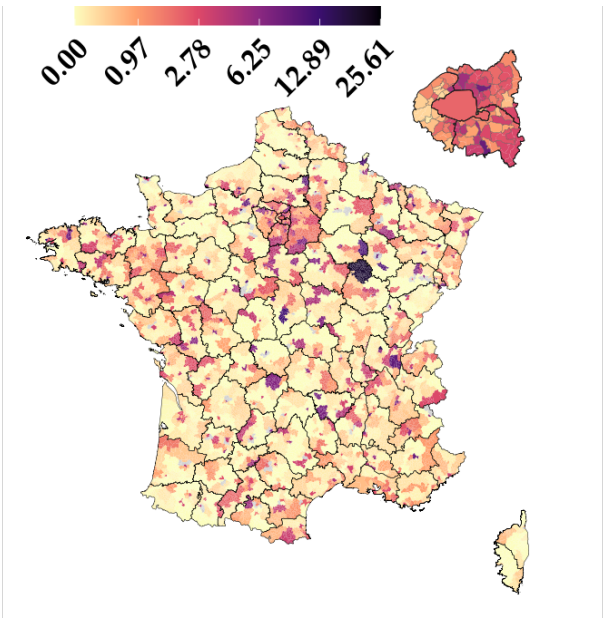


Figure 35 highlights differences across housing situations for the non resident French. Households in private rental face significantly higher expenses, often leading to negative resources left for consumption. In contrast, those in unstable housing exhibit lower housing expenses but also lower overall income. Social housing provides some relief in terms of expenses, mostly to Ukrainians, but overall income remains limited across all groups.

Figure 31. Distributions of age, income per CU, and income per CU without housing benefits for non-resident French

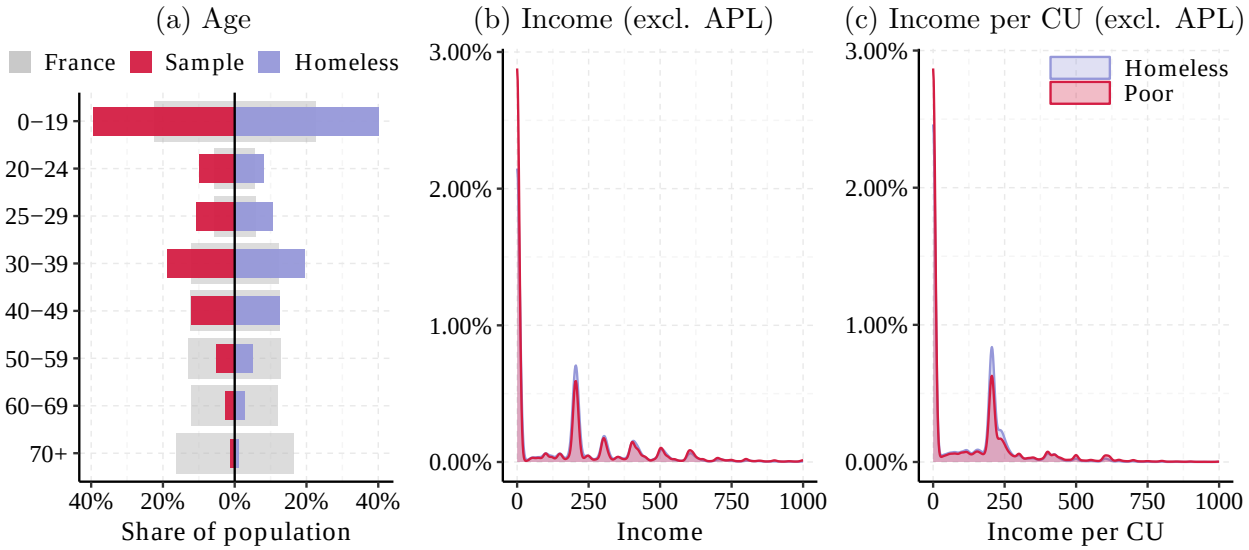


Figure 32. Distributions of consumption per CU.

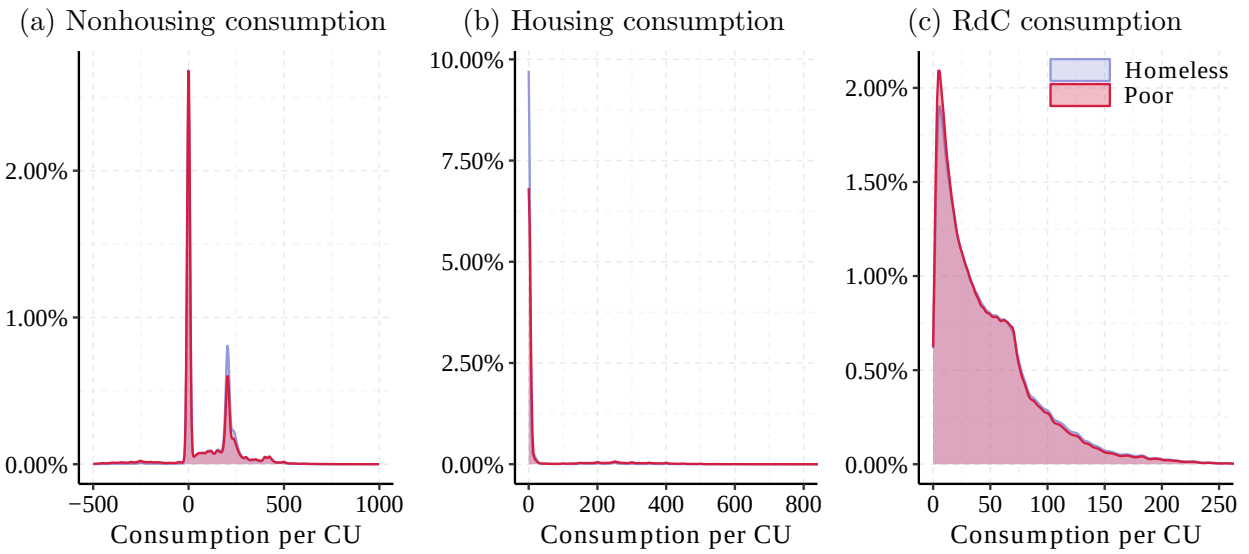


Figure 33. Decomposition of average income over the life cycle for non-resident French households

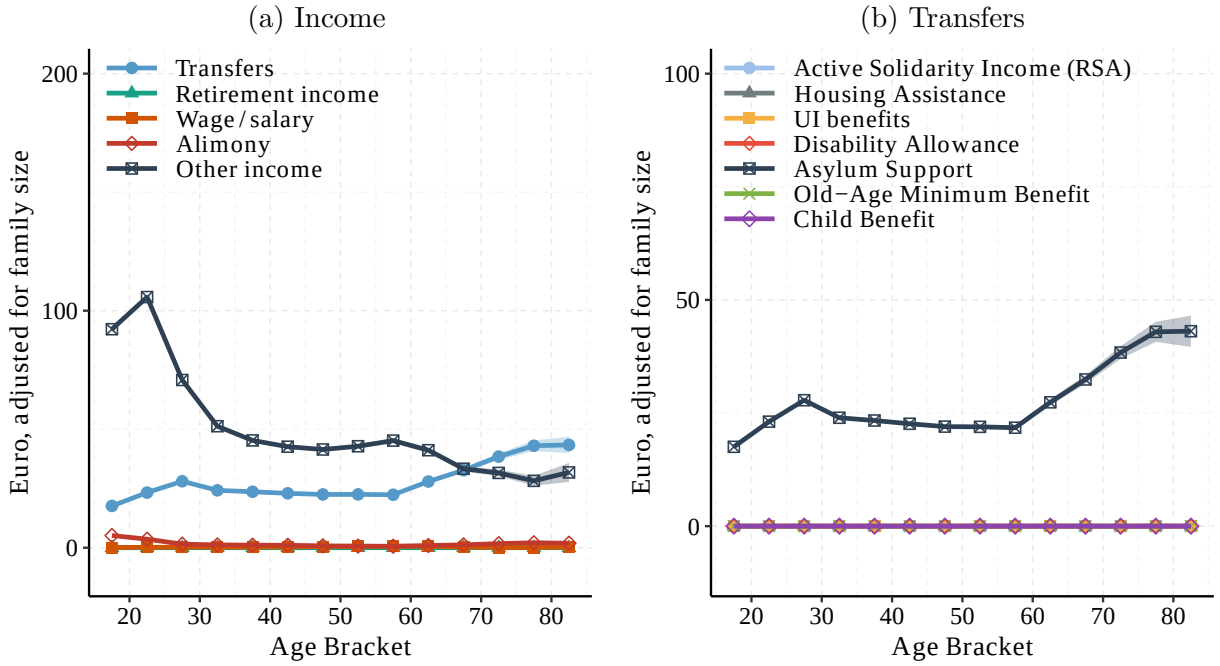


Figure 34. Decomposition of average expenses and consumption over the life cycle for non-resident French households

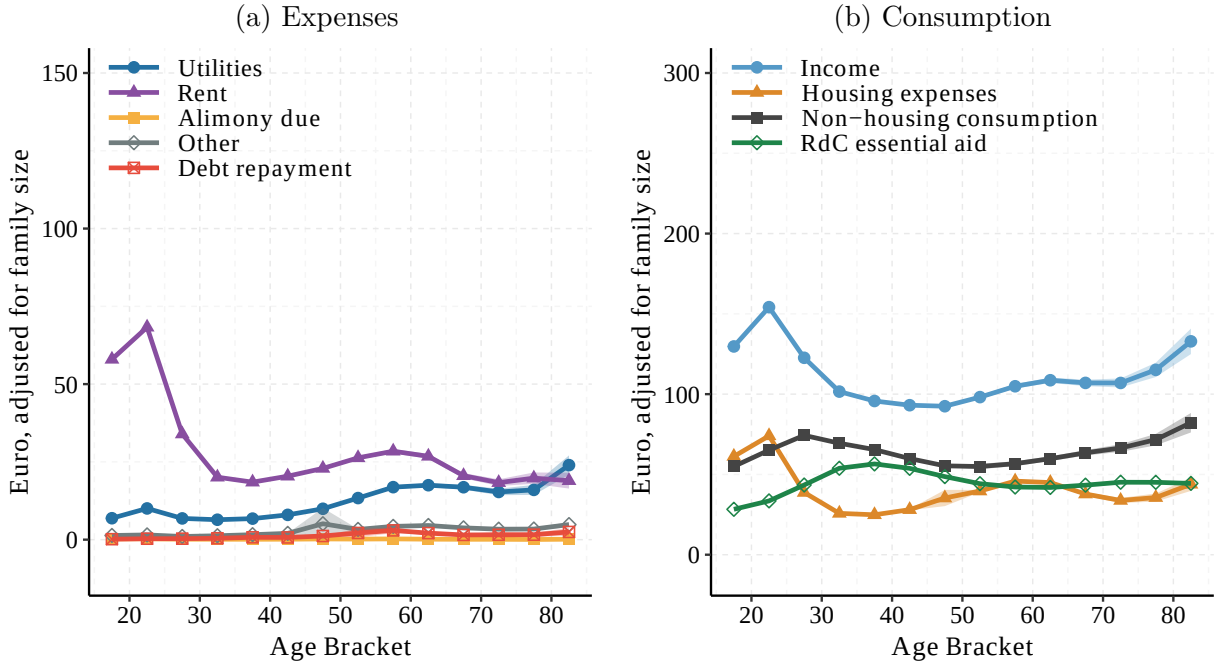
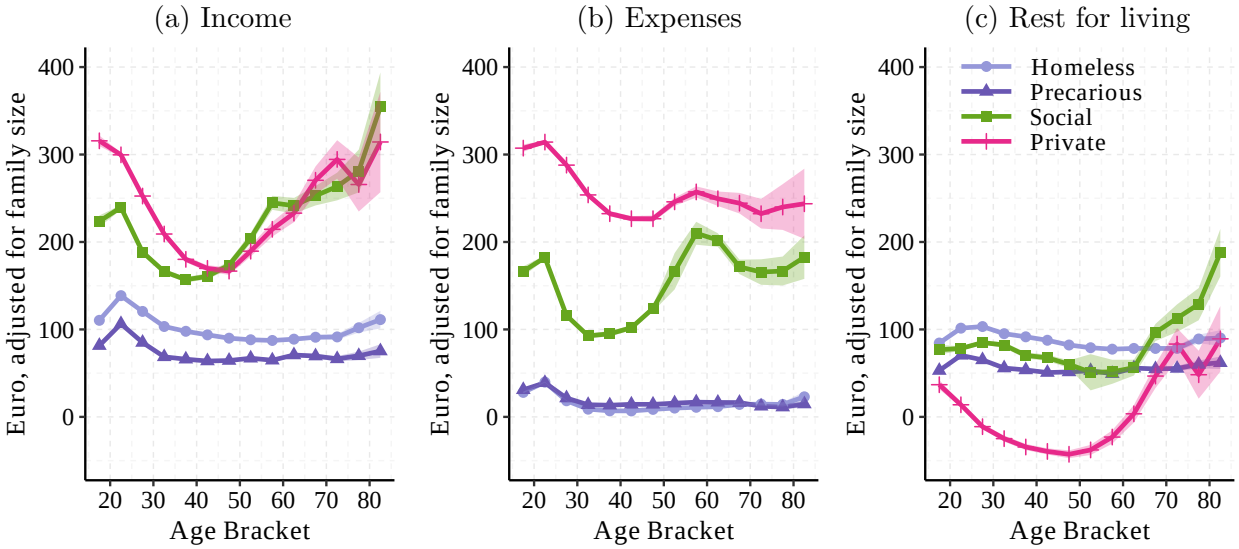


Figure 35. Life cycle average income, expenses, and rest for living by housing situation for non-resident French households



D Results: housing status decision

Table 12. Determinants of housing tenancy

Variable	Private	Social	Unstable	Precarious	Homeless
Demographics.					
Age (ref: 0–19)					
20–24	0.02***	0.05***	-0.07***	-0.04***	-0.03***
25–29	-0.01	0.08***	-0.09***	-0.07***	-0.03***
30–34	-0.01**	0.11***	-0.11***	-0.09***	-0.03***
35–39	-0.02***	0.12***	-0.13***	-0.10***	-0.04***
40–44	-0.03***	0.15***	-0.16***	-0.11***	-0.05***
45–49	-0.04***	0.18***	-0.18***	-0.13***	-0.07***
50–54	-0.06***	0.20***	-0.21***	-0.14***	-0.08***
55–59	-0.07***	0.21***	-0.22***	-0.14***	-0.09***
60–64	-0.08***	0.22***	-0.22***	-0.14***	-0.09***
65–69	-0.08***	0.20***	-0.21***	-0.13***	-0.09***
70–74	-0.07***	0.18***	-0.19***	-0.12***	-0.08***
75+	-0.08***	0.17***	-0.19***	-0.12***	-0.08***
Household type (ref: Couple)					
Single man	-0.05***	-0.08***	0.13***	0.05***	0.09***
Single woman	-0.07***	0.04***	0.04***	0.02***	0.03***
Number of children...					
... aged 0–3	-0.01***	0.02***	-0.01***	-0.01***	-0.00.
... aged 4–8	0.00	0.04***	-0.04***	-0.02***	-0.02***
... aged 9–12	0.01***	0.03***	-0.03***	-0.02***	-0.02***
... aged 13–16	0.02***	0.03***	-0.05***	-0.03***	-0.02***
... aged 16+	0.02***	0.04***	-0.05***	-0.03***	-0.03***
Citizenship (ref: French)					
EU citizenship	0.09***	-0.09***	0.03***	0.02***	0.01***
Other citizenship	-0.05***	-0.02***	0.10***	0.00**	0.09***
Unknown citizenship	-0.01**	-0.01***	0.02***	0.01***	0.02***
Student	0.16***	-0.09***	-0.09***	-0.10***	0.01
Retired	-0.04***	0.02***	-0.00*	-0.01***	0.00
Disabled	-0.04***	0.02***	0.01***	-0.00	0.01***
Duration in RDC.					
Not first spell	-0.02***	0.07***	-0.03***	0.00*	-0.04***
Spell duration in years					
1 year	-0.10***	0.38***	-0.35***	-0.18***	-0.17***
2 years	-0.12***	0.46***	-0.42***	-0.21***	-0.21***
3 years	-0.12***	0.51***	-0.47***	-0.22***	-0.24***
4 years	-0.13***	0.54***	-0.50***	-0.23***	-0.27***
5 years	-0.13***	0.56***	-0.52***	-0.23***	-0.28***
Finances.					
Income w/o housing benefits:	See Figure 14.				
In debt	-0.03***	0.09***	-0.03***	-0.02***	-0.01***
Debt repayment (CU)	-0.00***	-0.00***	0.00***	0.00***	0.00***
Local variables.					
Log Food CPI	0.02	0.04	-0.08.	-0.00	-0.07
Log unemployment	0.04**	-0.08***	0.04*	-0.01	0.05*
Log local revenue	-0.02	-0.01	0.01	0.02	-0.02
Log firm creation (other)	-0.01***	0.01.	0.00	0.00	-0.00
Log firm creation (sole proprietorship)	-0.01*	-0.02***	0.03***	-0.02***	0.04***
Log firm stock (per k hh)	0.03	-0.01	-0.03	-0.05**	0.03
Log private units (CAF) (per k hh)	0.07***	0.04.	-0.10***	0.05***	-0.15***
Log private listings (per k hh)	0.02***	0.00	-0.01*	-0.00	-0.01
Log social housing stock (per k hh)	-0.03.	0.10***	-0.05***	0.01	-0.07***
Shelter capacity (per k hh)	-0.00	0.00	-0.00	0.00.	-0.00
Log private rent (€ per sqm)	-0.08***	0.00	0.07**	-0.05***	0.12***
Log private rent per sqm (CAF, € per sqm)	0.15***	0.01	-0.16***	-0.04	-0.14**
Log social rent (€ per sqm)	0.05*	-0.01	-0.02	0.02.	-0.05*
Urbanization (ref: City Center).					
Suburb	-0.03***	0.02**	-0.01*	0.01**	-0.02***
Isolated city	0.01.	-0.03***	-0.00	0.01***	-0.02***
Rural	0.04***	-0.11***	0.00	0.02***	-0.02***

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.1$.
This table reports the estimation of model (3a) for each housing tenure (estimated by linear probability model). All models include (i) *period* and (ii) *canton* × *campaign type* (Winter or Summer) fixed effects. We also control flexibly for the probability of entering the RDC sample (at the time of entry) with a polynomial of order 3, and for the probability of remaining in the sample (for those who stayed) with another polynomial of order 3. Each model also include control variables for which we do not report the effect: education, weather (rain volume and average temperature in winter and summer), sectoral composition of the local firms, local number of households and share of retired households. We do not report the results for the few homeowner in the sample. subsample results.

Figure 36. Effect of age and spell duration on expenditures (housing, nonhousing, in charity)

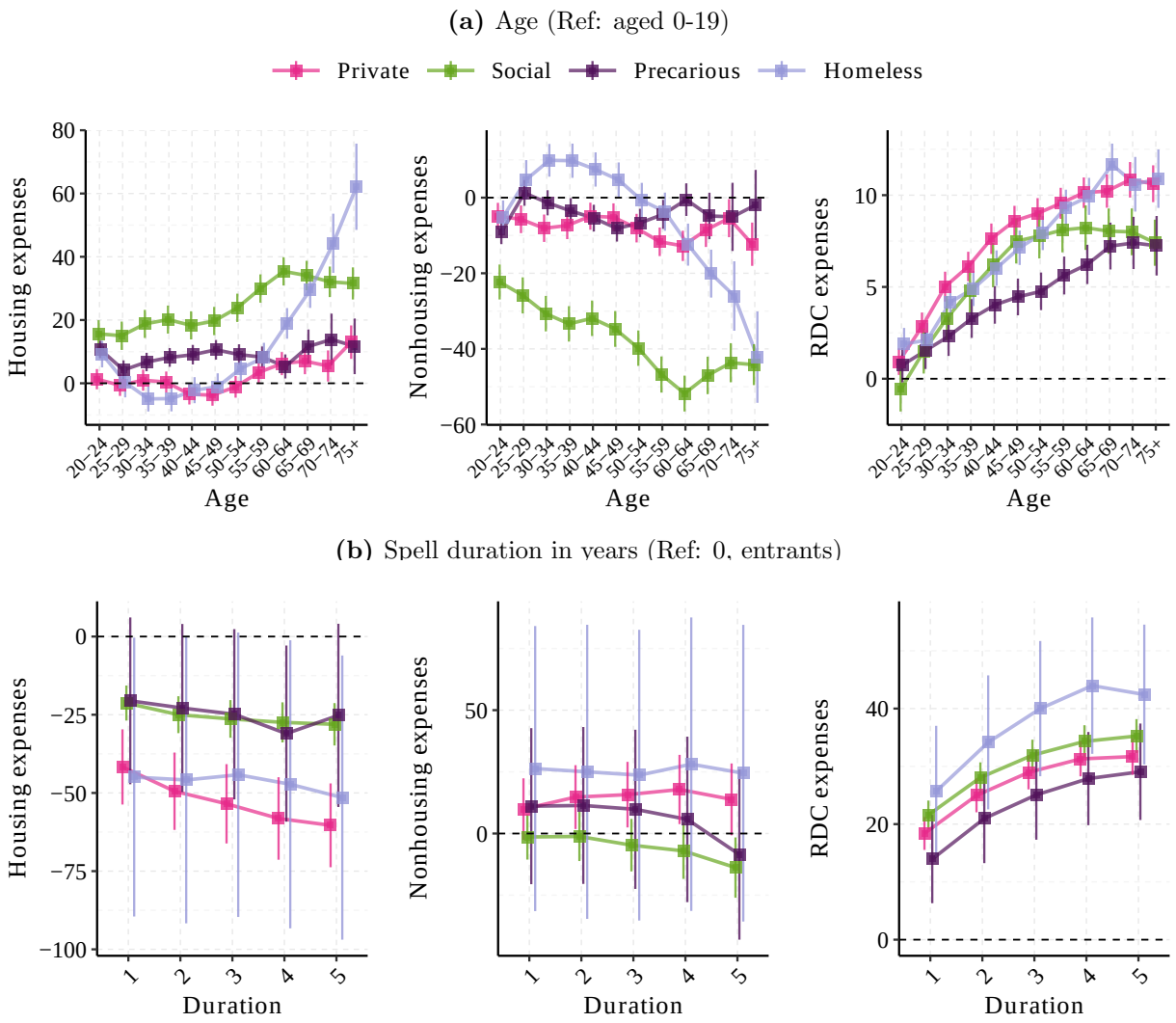
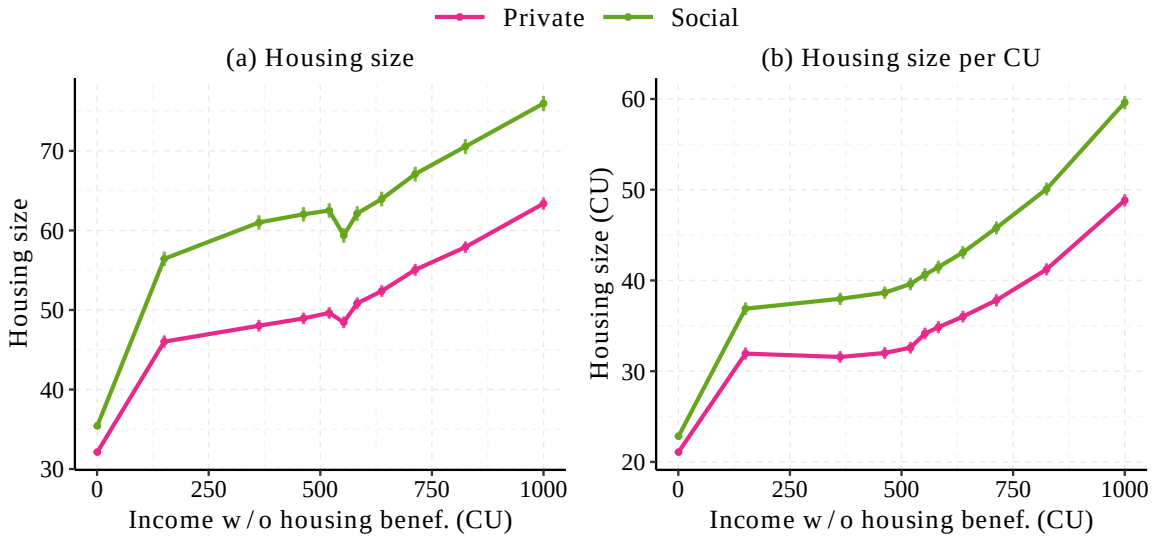


Figure 37. Predicted effect of income on (estimated) housing size



Note: for each household in private or social housing, we estimate the housing size by dividing the housing expenditures by the local market private or social rent, respectively. Then we run the same regression as for the housing expenses with these new outcomes (housing size and housing size per CU). As for Figure 14, the reported confidence interval corresponds to the confidence intervals around the income coefficients (with respect to the baseline of 0 income) in these regressions, not the confidence interval around the predicted housing sizes directly.