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Abstract

We offer new empirical facts and insights into the determinants and dynamics of *food and housing insecurity* in an advanced market economy, based on a novel administrative panel 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 document several findings. First, children and teenagers are vastly over-represented in both food and housing insecurity. Second, these situations are largely transient, though a very large fraction of households is exposed to the risk of experiencing them at some point in the near future. Third, flows into and out of food and housing insecurity are asymmetric: Inflows are highly sensitive to local macroeconomic conditions and policies, whereas outflows only depend on individual characteristics, with an especially strong duration dependence. Fourth, the high inflation rates of the past few years are responsible for about half of the fast rising rates of homelessness in France since 2018.

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"Aujourd'hui, on n'a plus le droit
Ni d'avoir faim, ni d'avoir froid."

Jean-Jacques Goldman, *La Chanson des Restos*

1 Introduction

While we have by now detailed knowledge of the dynamics of income and wealth at the top of the distribution ("the top 1%"), 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 ("the bottom 1%"). 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? Answering these questions is essential because, while the top of the distribution matters most for tax revenue, the bottom matters most from a social welfare standpoint. These questions are also 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 homeless individuals who may be without a place or a phone at which they can be reached. Administrative tax data also paint an incomplete picture of deep poverty because they exclude any individual without a tax identifier, for instance undocumented immigrants. Charity data can reach a broader population, but they often lack representativeness, e.g. because they are present in a single city or have an explicit religious affiliation. Moreover, they often have sample sizes that are too small to study heterogeneity across individuals or locations on a large (nationwide) 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 biannual panel data set, available in near real time, 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 a very 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 individual-specific and location-specific determinants of food and housing insecurity, as well as the efficacy of some policies aimed at alleviating poverty.

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's 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. In the main text, we generally focus on the subsample of documented residents; corresponding results for non-resident households are reported in the Appendix. Our first main finding is that *food insecurity (as defined by presence in our sample) and housing insecurity or homelessness are both transient phenomena; but these risks affect a surprisingly large share of the 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 around 50%; it is largest for homeless households and lowest – though with comparable orders of magnitude – for social housing tenants and older households. This means that the average duration of a spell of food or housing insecurity is relatively short: ∼17 months, or about 1.5 years, on average.[1] However, there are more than 5.5 million unique identifiers between 2018 and 2025 in our sample, a figure comparable to more than 8% of the overall French population (66.5 million inhabitants).[2] That is, a very large number of individuals have had to apply for temporary food assistance at our charity in the past 7 years. This means that at any given time, a very large share of the population is exposed to the *risk* of falling into extreme poverty over the next few years. The short spell duration and the large number of unique households in the panel are two sides of the same coin: If poverty spells are relatively short, the sample must be mechanically renewing a significant share of its observations and thus include a large number of new households in

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

[2] This calculation is slightly misleading, since the numerator includes undocumented households whereas the denominator does not. We cannot report a more accurate ratio, as it would indirectly reveal the share of non-residents in our sample, which we are not allowed to give. Despite this caveat, we view this statistic as particularly informative of the order of magnitude of the ex-ante risk of falling into extreme poverty within a few years.

each campaign.

Our second main finding is that *children and teenagers are overwhelmingly exposed to the risk of extreme poverty.* Both in our overall sample of residents and in the homeless subsample, the share of 0-9 year olds is between 20 and 25%. By contrast, the share of this age group in the French population is only 10%. This over-representation of children among the extreme poor is especially disturbing given the well-documented critical importance of early childhood development for future outcomes (Heckman et al., 2013; Hoynes et al., 2016).

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. 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, weather conditions, etc., to quantify their impact on the likelihood of entering and exiting deep poverty. More specifically, the source of variation we exploit to estimate these effects are the differential changes in economic conditions over time across locations.

This empirical analysis yields the third 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 or housing insecurity 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, the stock of social housing units, and the 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 an increase in both homelessness and food insecurity by about 10% (a one-for-one pass-through). A 10% increase in private housing rents has a similarly large impact. Conversely, a 10% increase in the stock of social housing units per capita reduces homelessness by up to 8%. The number of firms in a location has an even larger impact. By contrast, however – and this is our most striking finding – *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, households whose head

is older 60+ year-olds, those with zero income, and those who already spent 5+ years in the sample, have about 15 percentage point lower exit rates (from a baseline of about 37% per campaign) than the 20-year-olds, those receiving 600€ per consumption unit, and those who entered the sample for the first time, respectively. 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, individualized interventions.

Last, we use these results to evaluate how much of the dramatic rise in homelessness (strictly speaking) witnessed over the past few years (+61% for residents only between 2018 and 2023, the latest year for which we observe all of the local macroeconomic covariates) is due to food and shelter inflation. We construct a counterfactual rate of homelessness assuming that prices had remained fixed at their 2018 level. By sharply reducing entries flows, we would have had almost 20% fewer homeless households in 2023, all else equal. We conclude with the fourth and last main finding of our paper: *The recent acceleration of inflation, common to most advanced economies, accounts for about half of the total rise in homelessness observed during the 2018-2023 time period.*

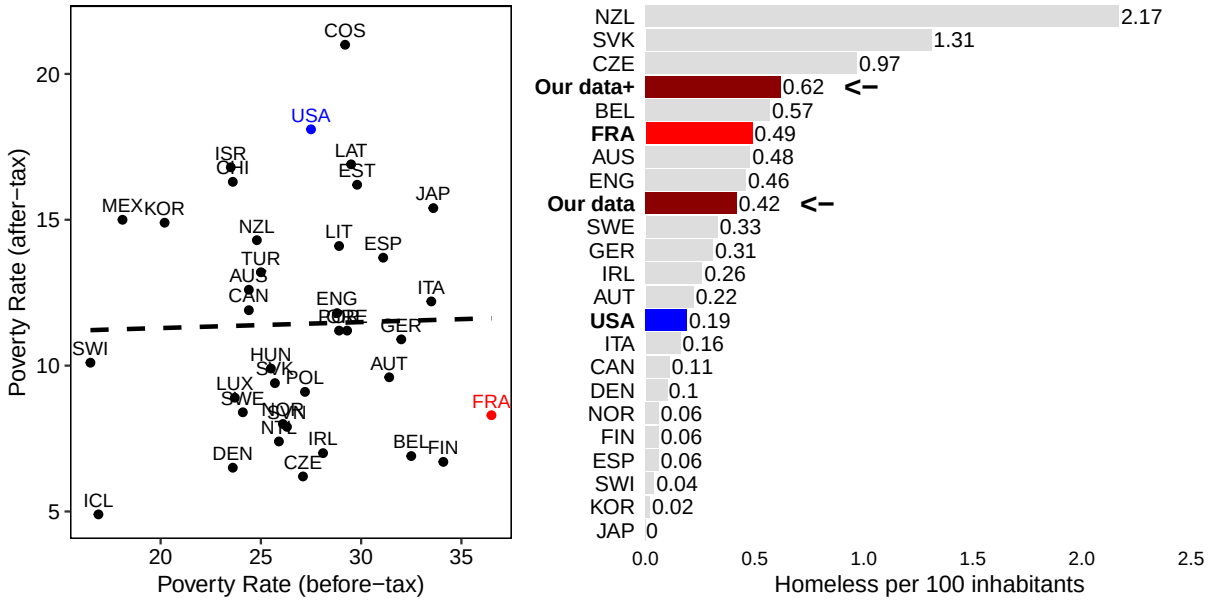
France in the OECD Context. Before moving on to the core of our analysis, we find it useful to place poverty and homelessness in France within the OECD context.[3] The left panel of Figure 1 shows the poverty rate in each country, defined as 50% of either median market income (horizontal axis) or median 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%), suggesting that it is one of the most redistributive welfare states. The U.S., by comparison, has a poverty rate that is in the average of 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 for 2022, 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 yields homelessness rates in 2022 between 0.42% using a definition as close as possible to theirs, and 0.62% if we add broader forms of housing insecurity (dark red bars; we provide further details about this comparison in Section A.3). For comparison, the U.S. estimate is given by the blue bar (0.19%). Note that different countries use different methodologies to measure

[3]Sources: here and here. Country-specific notes on the construction of the estimates of homelessness are available here. The French government estimates a similar number of homeless households: source here.

homelessness rates; for instance, the staggering 2.17% estimate for New Zealand includes broader forms of precarious housing in their definition, while the estimate for France focuses more restrictively on individuals sleeping in the street. We refer to the OECD website for a detailed discussion of their methodology for each country. While these estimates should be interpreted with caution – they can only give orders of magnitude and are not necessarily directly comparable to our own data – they nevertheless suggest that our sample captures a very large share (up to 80% of the total estimated by the OECD) of the homeless and, more generally, the housing-insecure households (127% of the OECD total) living in France.

Figure 1. Left: Poverty rates in the OECD (2022). Right: Homelessness rates estimated by 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 dark red bar labeled "Our data" gives the homelessness rate in our sample using a similar definition as the OECD. The dark red bar labeled "Our data +" gives the incidence of housing insecurity in our sample using the broader definition that includes all forms of insecure and inadequate housing.

Literature Review. Studying households facing food and housing insecurity is often hampered by severe data limitations (Hopper et al., 2008; Meyer et al., 2025a,c). Several important and ambitious empirical papers have recently been able to shed light on the homeless population specifically. Meyer et al. (2021, 2024) link 140,000 homeless individuals from the 2010 U.S. Census to administrative tax and safety-net records and tracks their characteristics and trajectories over time. Costantini (2025) studies the health and mortality outcomes of 300,000 mentally ill unhoused U.S. veterans. Roth (2026) links nationwide records of

homeless shelter requests in France with administrative employment data to study the impact of local labor market shocks on housing insecurity. Beauregard et al. (2026) construct an impressive data set to investigate the individual life trajectories leading to homelessness spells in British Columbia and Ontario, observed in a combination of hospital, shelter, and income assistance program data. Several papers study the drivers and consequences of evictions (Collinson et al., 2024, 2025; Humphries et al., 2024), housing programs (Cohen, 2024) or shelter access (Christopher et al., 2025) using data from specific U.S. cities or states. Our paper contributes to this rich and growing literature by using large-scale, nationwide panel data for France, following millions of individuals over several years and across a large spectrum of situations ranging from homelessness strictly defined to broader conditions of food and housing insecurity. This data set allows us to exploit the substantial cross-sectional variation in local macroeconomic conditions across an entire country to establish the impact of economic shocks on these outcomes.[4] Our data also contain undocumented individuals who may be difficult to observe in administrative samples.

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 require as 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. Our paper provides some of these moments, which are central for evaluating the effectiveness of government welfare programs or charities' food assistance (Prendergast, 2017, 2022). 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 and advocated using a consumption-based definition. As eligibility to the charity we study is based on measured consumption, our data naturally satisfies this criterion.

Outline. In Section 2, we introduce our data and provide institutional context and summary statistics. Section 3 describes our econometric specifications. In Section 4, we estimate the impact of local economic shocks and individual characteristics on entry into and exit from food and housing insecurity. Additional findings for resident households are gathered in Appendix A, and corresponding results for non-residents are reported in Appendix B.

[4] Blank (2005) highlights the importance of studying the role of place and local shocks and characteristics in shaping poverty.

2 Data and Summary Statistics

2.1 Terminology

Before describing our data, it is helpful to define at the outset the precise terminology that we will be using throughout the paper.

Food Insecurity, Housing Insecurity, Homelessness. The individuals we observe in our sample are those who face severe deprivation to the point of requesting free food assistance from a charity. Thus, by *food insecurity*, we simply mean "presence in our sample". By *homelessness*, we mean people sleeping rough (in the street or a public space), or in emergency accommodation (overnight shelter, hospital, or hotel room). By *housing insecurity*, we mean people who are either homeless or in any other form of short-term, precarious, or inadequate housing (women's or migrant shelter, halfway house, hosted by family or third party, subletting, in shared housing, threatened with eviction, in illegal housing, caravan, mobil-home, tent, makeshift dwelling, squat).[5]

Residents, Non-Residents. Because they are such different populations (in particular regarding their eligibility to government transfers), we separate the sample between (documented) residents, on the one hand, and (undocumented) non-residents, on the other hand. We do not have an explicit variable indicating legal residency status in our data set. We thus consider that an observation is a resident if they are either (i) a French citizen; (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 may slightly overstate the number of non-residents by including 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. We specify at the beginning of each section whether the results are for the full sample or either of the two-subsamples. We respect RDC's policy of never revealing the respective shares of French citizens, residents, and non-residents in the sample.

[5]This classification of housing situation follows the European Typology of Homelessness and Housing Exclusion (ETHOS). We sometimes refer to non-homeless forms of housing insecurity as *precarious*.

2.2 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). The critical feature of this charity, for our purposes, is that households are eligible to receive food assistance for the next semester if their resources at the time they apply are below a given threshold. This particular rationing criterion leads RDC to collect data biannually (with a "summer" campaign starting in March and a "winter" campaign starting in November) on a wide range of characteristics of the individuals who apply for support. If, at the end of a period, an individual decides to re-apply for another semester of food assistance, they need to provide updated records. RDC has digitized and anonymized these data since 2018, with partial digitalization in 2017.

Institutional Context. RDC 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.[6] The data they collect allow us to observe a very large share of the very poor households in France, and, as we argue below, most of the homeless. RDC is by far the largest food assistance charity in France, and the *only* one that is completely free of charge for 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, and is open to all.[7] All of these characteristics make RDC a likely "first stop" for food assistance.[8]

The left panel of Figure 4 shows the network of its local drop-in centers (*centres d'accueil*). The black (respectively, red) dots give the location of those that already existed at the beginning of our data set (resp., those that opened between 2018 and 2023). In 2023, there were 1928 RDC drop-in centers dedicated specifically to food distribution across mainland

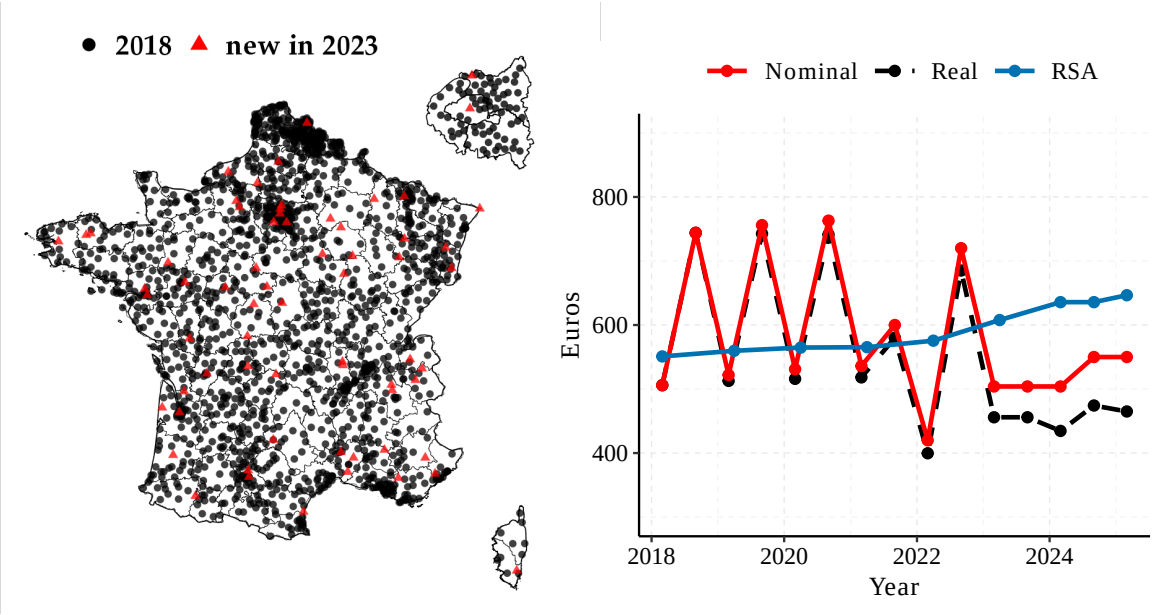
[6]Households receive approximately one meal per person per day, generally consisting of 100 grams of protein product, 100 grams of vegetables, 100 grams of dessert, and either 1 yogurt or 30 grams of cheese or 20 grams of cream.

[7]By comparison, getting food aid from the Red Cross requires a certificate from a social worker, and some of their local branches only serve certain groups (e.g., women affected by domestic violence). Moreover, their food aid strategy relies on food parcels given in exchange for a financial contribution. For the lowest-income households, even a 4€ contribution can be a significant barrier. Most other associations also ask people to show supporting documents or administrative paperwork, or require them to go through a social worker first – a bureaucratic process that is often at least as burdensome as RDC's.

[8]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 drop-in centers in the country, vs. more than 2,300, including 1,928 dedicated to food distribution, for RDC (source here). The third largest charity, the Red Cross, has 629 food distribution centers as of September 20, 2026 (source here). Note that households may receive food assistance from both RDC and other charities.

France. This represents an average of 1 center per 34,000 inhabitants and 1 center per 110 square miles (or 286 km^2), meaning that, if they were evenly distributed across space, everyone in the country would live within 11 miles (or 17 km) of an RDC center.[9] About 43% of the drop-in centers are in city centers, 27% are in suburbs, 18% are in isolated cities, and 12% are in rural areas.

Figure 2. Left panel: Territorial grid of RDC drop-in centers. Right panel: Eligibility threshold for single without children.



Notes: Paris and its neighboring suburbs are expanded on the top right of each map of the paper (left panel). Up through 2023, the eligibility threshold was higher in the winter than in the summer to reflect the higher heating costs (left panel).

The eligibility criterion is based on the household's family composition and their "rest for living" (*"reste à vivre"*), defined as the difference between all income sources and recorded expenses. To be eligible in the winter 2024 campaign, the household's rest for living must be lower than a nationwide threshold of about 500€ per month for a single individual and between 600–650€ for a couple with no children.[10] These eligibility rules are illustrated in the right panel of Figure 4. The red line shows the evolution of the monthly eligibility threshold for a single individual without children (with inflation adjustment in black). For reference, the blue line reports the amount of RSA monthly cash transfer, one of France's

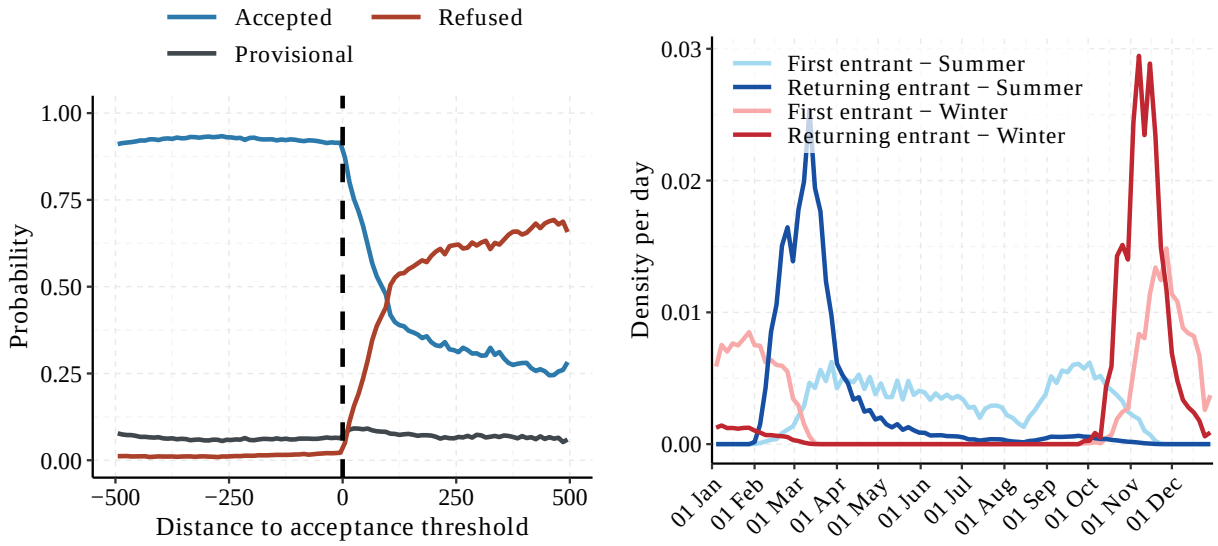
[9]Of course, neither the drop-in centers nor the population are evenly spaced. In Figure 22 in Appendix A.1, we compute the distribution of distances between each French household and their nearest RDC drop-in center. We find an average distance lower than 6 miles (10 km), with almost every household located within 12 miles (20 km) of a drop-in center. Figure 22 shows that the distance to the nearest Red Cross center is significantly larger. Technical details on how these distances were computed are described below the graphs.

[10]We respect RDC's policy of not revealing the exact eligibility thresholds.

major redistributive policies described in more detail below. If a household's rest for living is above the threshold, a collective decision is made by the volunteers as to whether to grant eligibility, giving rise to a kink rather than a sharp discontinuity in the number of recipients, as shown in the left panel of Figure 3.[11]

The right panel of Figure 3 shows the distribution of entry dates into the sample. Most of the households who re-apply to RDC for a new (summer or winter) campaign do so within the first two months of the campaign (March or November, respectively). First-time applicants are much more evenly distributed between the start dates of two consecutive campaigns, especially so in the (longer) summer campaign. Figure 20 in the Appendix also reports the fraction of time that households visit their RDC drop-in center during a campaign to collect food.

Figure 3. Left panel: Probability of acceptance as a function of the household's resources net of their eligibility threshold (French residents only). Right panel: Distribution of enrollment dates.



Notes: The structural break at the eligibility threshold (left panel) is under-estimated as we did not correct for the potential self-selection of applicants who choose not to apply if they presume that they will fall to the right of the eligibility threshold. The winter campaigns last 18 weeks and the summer campaigns last 34 weeks (right panel).

Variables in the RDC Data. First, RDC assigns 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

[11]The size of the kink does not appear to be affected by any of the individual or location characteristics that we observe (see in particular Figure 18 in the Appendix). 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.

move to a different location (they can only receive food from the location to which they applied in the latest campaign), or when they form a new household after, e.g., getting divorced or leaving their parents' household.[12] 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 – in particular, we do not directly observe why they no longer apply for food assistance from RDC nor their subsequent trajectories. This is the main limitation of our data.

Second, we observe several socioeconomic characteristics of the applicants. We know the birth date and gender of each household member; and for the household head, we observe their zip code, citizenship (French, other EU citizen, or Other), usual language spoken at home, highest educational degree, health insurance coverage, and disability status. The data also 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, we observe the income and some expenses of each household member. Income consists of wages, pensions, all categories of government transfers ("RSA", a cash transfer described in more detail below, as well as housing, unemployment, child, disability, old age, and asylum benefits), alimony received, and "other regular income". Observed expenses consist of rent, mortgage, housing and property taxes, other housing expenses (e.g., hotel rooms), 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.

Fourth, applicants report their housing situation. They can be homeless, housing insecure, social housing tenants ("*logement social*"), private housing tenants, or homeowners. We defined homelessness and housing insecurity earlier. Social housing (mostly "*habitation*

[12]For robustness, we also constructed an alternative identifier based on household characteristics that are fixed or of which we can keep track relatively consistently over time, such as birth date, zip code, age of the children and other family characteristics. This allows us to mitigate the concern that some returning recipients may be assigned a newly created identifier after (say) losing their RDC identification card and not being able to justify their identity, which would fallaciously shorten their observed poverty spells in our sample. We find that at most 5% of the households can be associated to several such synthetic identifiers at different points in time based on their observable characteristics. The main results of this paper, in particular our duration analysis, are not significantly affected by the choice of identifier.

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 of the dwelling, is on average equal to 75% in 2022-23.[13] 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.[14]

Reporting Accuracy. 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 a first or a new enrollment. For instance, if they report earning a certain level of income that should make them eligible to some welfare benefits, they must show proof that they are indeed receiving these transfers (and if they are not taking them up, RDC can provide administrative support to do so). Such verification is, however, naturally more difficult for non-residents, e.g. undocumented immigrants who are not eligible to receive any transfers; in such cases, RDC relies on their self-reported information. Nevertheless, we find evidence in the Appendix of a bunching mass at the eligibility threshold, which could indicate some amount of misreporting (either on the part of the applicants or the volunteers). We also find bunching at the previous campaign's eligibility threshold, suggesting a learning mechanism.[15] That said, even if there is bunching at the threshold, the mere act of applying for food assistance is, itself, a clear indicator of food insecurity. Hence, such reporting concerns should not affect the analysis of entry and exit flows nor the duration analysis studied in this paper.

Sample Representativeness. Appendix A.3 discusses the extent to which our data is a selected sample of the poor living in France, by comparing them to aggregate summary statistics from other charities and research institutes, existing survey data (HFCS and EU-SILC) and, for homeless individuals, independent OECD and government estimates. Our first main

[13] INSEE estimated that in 2006, the ratio of social to private rents, controlling for location and various characteristics, was on average equal to 54% (source 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.

[14] Source here.

[15] Preliminary results obtained by merging our sample with the French welfare benefit data (CAF) using observable location and family characteristics of the recipients show, however, that self-declarations by RDC recipients are largely consistent with these administrative records.

findings is that a number of key descriptive statistics from our sample are broadly consistent with those found in the reports of other institutions.[16] Our second main finding is that extreme poverty and housing exclusion are severely and systematically under-represented in survey data; in other words, we believe our sample gives a much more accurate picture of the bottom tail. Our third main finding is that our data set captures an extremely large share of the homeless population in France, around 80% of the estimate provided by the OECD in 2022 (see Figure 1). To conclude, while it is difficult at this point to establish with certainty the representativeness our sample, we believe the sheer size and scope of the charity – the largest in the country by a wide margin – implies that significant sample selection is unlikely. Regardless, this data set provides invaluable insight on food and housing insecurity.

Additional RDC Surveys. RDC runs additional quantitative and qualitative surveys on a small sample of about 1,500 recipients.[17] 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. Because this survey also contains several covariates that are present in the main data set, we are able to partially merge these two samples, thus giving us additional information about the recipients. Our results so far only use the survey as an independent source of additional descriptive information.

2.3 Local Economic Characteristics

Our empirical analysis leverages RDC's fine territorial grid: We correlate the spatial variation in the incidence of food and housing insecurity to that of a multitude of local economic characteristics. To this end, we merge our main data set with several additional data sources. We start by defining our baseline geographical unit.

[16] In current work in progress, we compare our sample to the recipients of welfare benefits in the administrative CAF data. Our results at this stage are too preliminary to warrant further discussion.

[17] This subsample is not random, e.g., it overweights French-speaking individuals. We explore the characteristics of the population in this survey in the Appendix.

Geographical Unit. Our baseline definition of a local area is the *bassin de vie*, or "living basin", defined by the INSEE[18] as the "smallest territory where residents have access to the same range of common essential everyday services and facilities, such as personal services, commerce, education, health, sports, recreation, culture and transport".[19] The Paris living basin contains not only the city of Paris but also several of its suburbs (a total of 439 municipalities).[20] Because this covers a large and very heterogeneous area, we augment this official definition by splitting the Paris basin into several smaller entities: the city of Paris itself, on the one hand, and the 24 administrative *arrondissements* for the remainder of the region.[21] In the sequel, we refer to this construction as "augmented living basin", or ALB. Overall, there are 1,728 ALBs in 2023 (their exact boundaries vary over time). On average, they are 320 km^2 (124 square miles) large and contain 23,673 households and 304 RDC recipients.[22] Figure 4 gives the number of food insecure and homeless RDC recipients in 2023, respectively, as a share of the local population (i.e., the number of households in the corresponding ALB). These maps show a significant amount of spatial variation: The most distressed areas count up to fourtyfold more RDC recipients and twentyfold more homeless households, as a share of the local population, than those at the other end of the spectrum.[23] These two maps are far from perfectly correlated, so that the variation in the share of homeless households is not mechanically driven by the share of RDC recipients in the area (and hence by the potentially endogenous location of RDC drop-in centers).

Housing Market. 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 government transfers. We can therefore measure the average rents of private housing units at the local level (ALB, defined above). 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

[18] National Institute Statistics and Economic Studies.

[19] This is roughly equivalent to a commuting zone in the U.S. All of the results of our paper are robust to alternative definitions of the local area, e.g., *bassin d'emploi* ("employment basin") or *canton*.

[20] Source here.

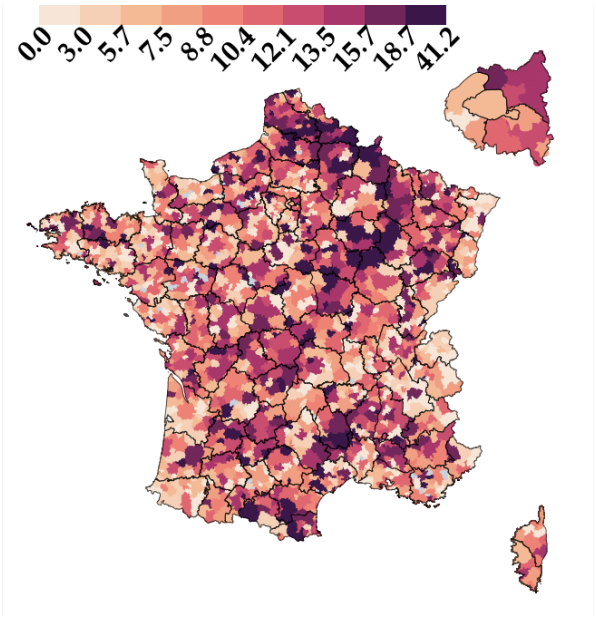
[21] This is an administrative subdivision managed by a sub-prefect to help the national government deliver services locally (see definition here). They should not be confused with the more commonly known *arrondissements* inside the city of Paris! When the frontier of the Paris basin intersects an arrondissement, we construct the relevant local area as the intersection of the two entities.

[22] The median number of RDC recipient households per ALB is 82 in 2023. A larger administrative entity that we sometimes use is the *département*. There are 96 départements in mainland France; they are 2,220 square miles large and contain 320,000 households on average.

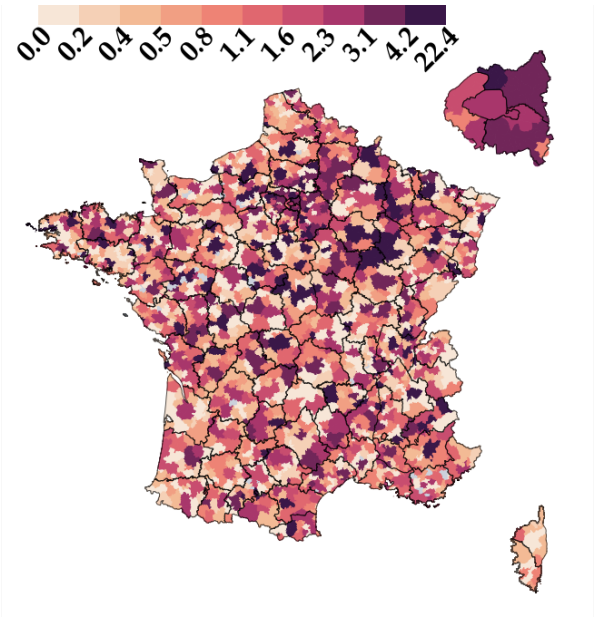
[23] Recall that the share of homeless households in our sample is 4.2 per 1,000 households.

Figure 4. Spatial coverage and intensity of RdC activity.

(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.

private units available for rent at the zip code level, obtained from the systematic scraping of online listings.[24] This allows us to measure the rents of vacant units, which homeless individuals can potentially move to, as opposed to the rents of currently occupied units reported in the CAF sample. Furthermore, publicly available government data give us the distribution of rents of occupied social housing units at the local level.[25] We also observe, in each location, the stock of social housing as well as their vacancy rate. Finally, we collected administrative data on the number and capacity (total number of slots) of homeless shelters (*Centres d'Hébergement et de Réinsertion Sociale*, or CHRS).[26] All of these variables are at the annual frequency, except for the CAF rents that we can compute biannually.[27] Figure 5 shows examples of spatial variation of two of these variables across ALBs: private rents (from online listings), and the number of social housing units. Unsurprisingly, rents are highest in the Paris area and other large cities, along the French Riviera (*Côte d'Azur*), and the Alps.

Food Prices. Second, in order to explore the role of food inflation in driving poverty, we purchased bar-code-level scanner data of Worldpanel by Numerator, provided through the

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

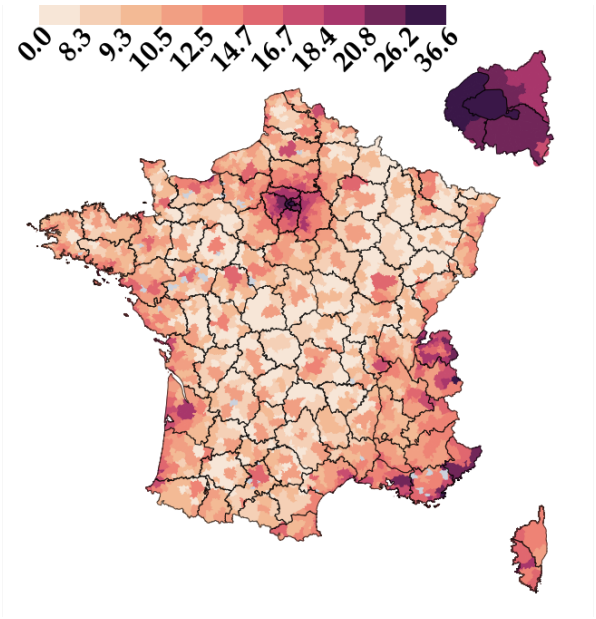
[25] Source: here.

[26] Sources: here and here.

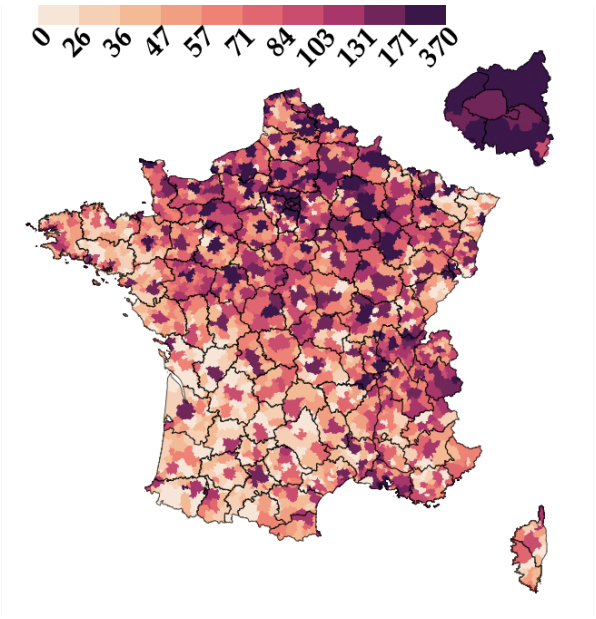
[27] We associate the local average CAF rent in June of a given year to the winter (November) campaign of that year, and in January for the summer (March) campaign.

Figure 5. Selected local (ALB-level) housing variables.

(a) Private rent (from listings in €/sqm)



(b) Social housing units/1,000 households



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

Aimark Foundation. 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. We aggregate these prices at the *département* level (see footnote 22) and the yearly frequency. These data allow 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 left panel of Figure 6 shows the spatial variation of the food inflation rate between 2018 and 2023.

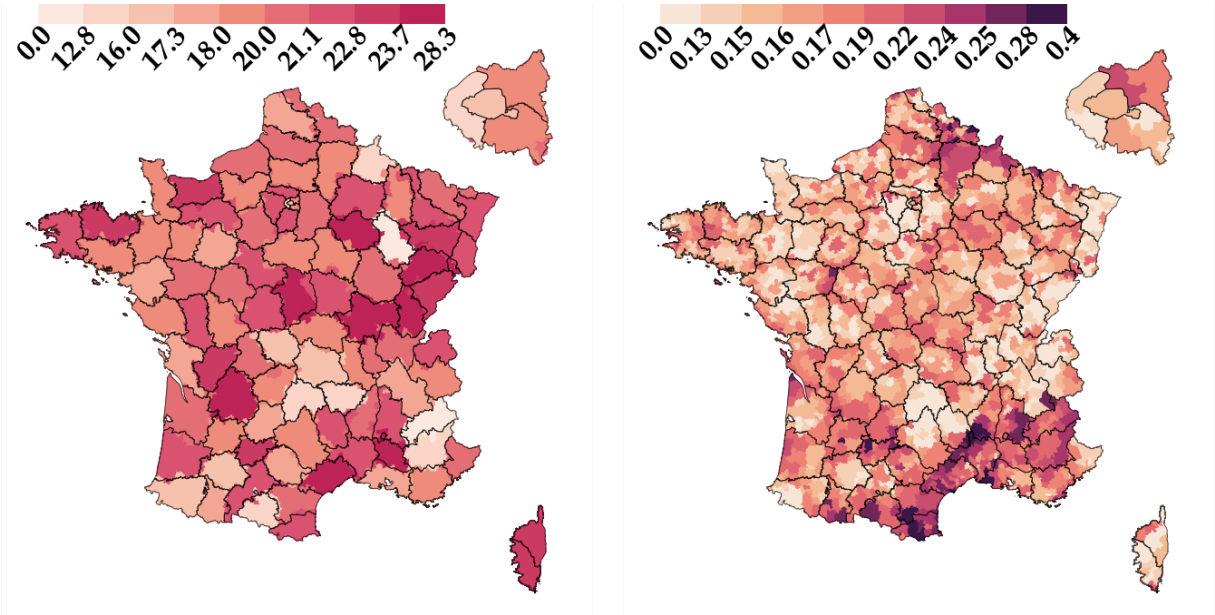
Other Local Variables. Third, we merge our data with several other local covariates (all at the ALB level): average income per capita, population size and density, unemployment rate, inequality, gas prices, stock of firms, business creation and destruction (sole-proprietor or other firms), sectoral composition, temperature and rainfall, public amenities, election results.[28] The right panel of Figure 6 show the spatial variation of the unemployment rate

[28]Municipal elections took place in 2008, 2014, 2020, and 2026. Most of these local data are publicly available on the data.gouv.fr website. The unemployment rate is computed using data from France Travail.

in 2023; it is particularly high in the northern suburbs of Paris, the north-eastern part of the country, and along the Mediterranean coast.

Figure 6. Selected local (ALB-level) economic conditions.

(a) Food inflation (2018-2023) (b) Unemployment rate (cat. A, B, C)



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

2.4 Selected Summary Statistics

The first paragraph of this section reports the overall number of food-insecure, homeless, and housing-insecure individuals in our sample.

Sample Size. The left panel of Figure 7 plots the evolution of the number of RDC applicants over time (black line), and the number of accepted recipients (blue line).[29] 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 7 also reports the overall number of housing insecure individuals in our sample: about 300,000 homeless (light purple line), and between 400,000 and 500,000 housing insecure (dark

A detailed discussion of our definition of unemployment is provided in footnote 34. We also relied on OFGL for the most recent population data, INSEE for the stock of firms and new creations as well as amenities, Piketty and Cagé for local inequality, French Ministry of the Interior for crime and delinquency. To compute firm destruction, we use records from INPI, which include all cessations and radiations, rather than the (far too small) number of firm deaths reported by INSEE.

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

purple line); the latter amount to 0.62% of the population, or 1 per 150 inhabitants. The historical annual reports of RDC allow us to report the number of recipients and housing insecure individuals as far back as 2009. Overall, our data contains 5,575,625 unique individuals (respectively, 1.94 million experiencing housing insecurity) across all campaigns between winter 2017 and winter 2025, i.e., about 8.3% (resp., 2.9%) of the French population in 2025. We interpret these sobering values as the share of individuals who were *at risk* of falling into food insecurity (resp., housing insecurity) within the last 8 years.[30]

Notice that the post-pandemic period has been marked by a very large increase in the number of food insecure households: +37% between 2018 and 2025, on average across both campaigns of each year.[31] The increase in the number of housing insecure recipients has been even larger: +63% between these two dates. 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 7 shows that a non-negligible share (about 20%) of the jump in food insecurity in 2022 resulted from the immigration of Ukrainian refugees in France following the invasion of their home country by Russia.

Demographic and Location Characteristics (residents). Table 1 presents basic summary statistics for *residents* only (averaging across campaigns) both for the overall sample and for three sub-samples defined by specific housing statuses: private renters (29% of the sample), social housing renters (43% of the sample), and housing insecure households (22% of the sample); the remainder (5%) are homeowners. The corresponding results for non-resident households are reported in Appendix B.1.

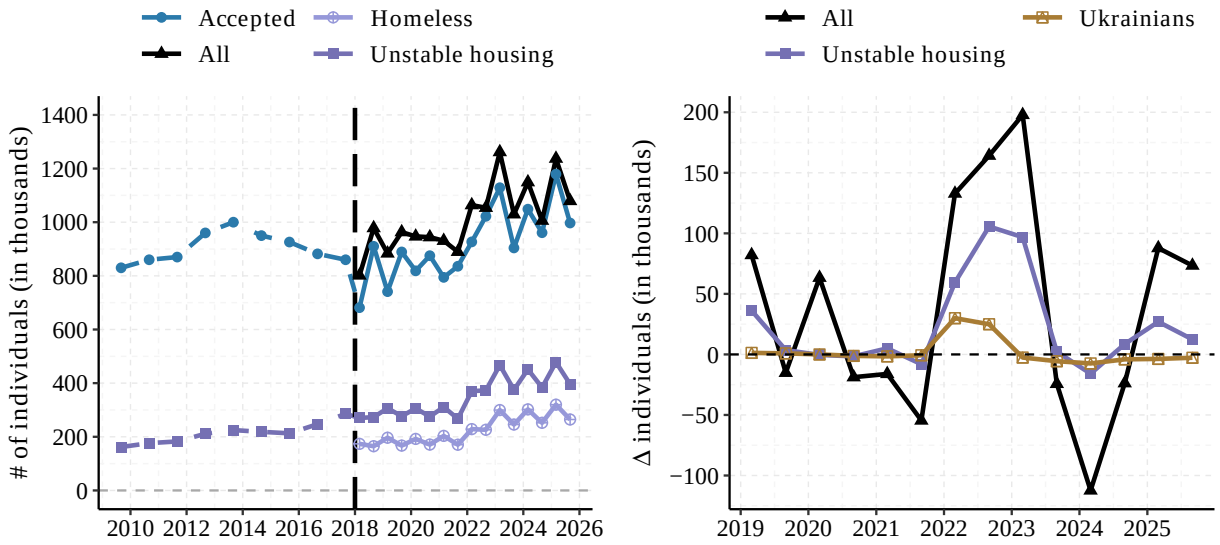
Starting with demographic characteristics, we find that resident RDC recipients are 45 years old on average (vs. 55 for the overall French population); 33% of them live in a couple (vs. 59% for the French overall); they have one child on average, 18% of whom are younger than 3 years old. Social housing tenants are more likely to be single women (49% vs. 41% in private housing and 36% in housing insecurity), older, and with children. The subsample of housing insecure recipients is younger (40 years old on average, with a share of students that is almost twice as large as in the overall sample), more likely to be single men (33% vs. 24% for the overall sample),[32] and less likely to be disabled (4% vs. 9% in the whole sample).

[30]Notice that this calculation counts RDC recipients in the numerator, including the undocumented immigrants, while the denominator does not include them. We cannot provide the corresponding figure for documented residents only as it would reveal their share in the population, which would infringe RDC's policy. We nevertheless find this staggering 8% value particularly suggestive and useful.

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

[32]The share of single men is even higher (46%) if we restrict the sample to French citizens; the difference

Figure 7. Left panel: Number of observations (accepted recipients and all applicants). Right panel: Impact of the invasion of Ukraine by Russia on the rise in food and housing instability.



Note: The left panel shows the total number of applicants (black), those accepted into the program (blue), those in housing insecurity (dark purple), and those experiencing homelessness (light purple). Data before 2018 come from RDC's 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.

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 7.5% of the recipients live in rural areas (these are more likely to be older), vs. 21% for the French overall. That is, despite the relatively strong presence of the charity in rural areas, 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 more likely than the other groups to live in isolated cities or rural areas. Finally, RDC recipients regardless of housing status tend to live in slightly poorer and less economically active areas, with lower income per capita and higher unemployment.[33,34] Finally, Table 5 in Appendix A.1 summarizes the

is explained by a larger share of couples among non-French residents.

[33]Note that France has a larger GDP per capita than the 17k€ value reported in the table – between 35k and 40k€ 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. Using instead average annual income per household (instead of per capita) we find 29k€ for France and 27k€ in our full sample.

[34]The value reported in the table for the unemployment rate in France (18%) uses a broad definition that includes marginally attached workers and is larger than the official figure (8%). The latter is 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 ALB level; instead, we rely on France's administrative data and *France Travail*'s official

migration rates conditional on remaining in the sample. We find very low rates of mobility across space: About 1.2% of the resident households move to a different zip code, and less than 0.1% move to a different département, in a given year. By comparison, migration rates across départements are around 1% annual in the DADS (matched employer-employee data).

Age Distribution (residents). Beyond these averages, we are interested in the *distribution* of some of the demographic characteristics of the sample population. One variable that turns out to be particularly interesting is age. The left panel of Figure 8 shows the age distributions in the overall resident sample (red), in the homeless sub-sample (blue), and in the overall French population (gray). We observe that there is an overwhelmingly large share of children (ages 0 to 9) and teens (ages 10 to 18) in our data relative to the overall French population. Specifically, there are between 20-25% children younger than 9 years old, both in our sample and (to an even larger extent) among the homeless, while their share in the overall population is only 10%. In other words, children and young adults are more than twice as exposed to food and housing insecurity in France as the population average – a particularly troubling fact given the critical importance of the first few years of life for the acquisition of human capital (Heckman et al., 2013), and of labor market entry for the individual's subsequent career path.[35]

The right panel of Figure 8 focuses on the age distribution among 0-to-18-year-olds, and splits each age group by family structure: single mother, single father, couples with 1, 2, or 3+ children, or no parent. About a third of the children in both food and housing insecurity (and up to a half at older ages) are in single-mother households. Most of the others are raised by couples in with 3 or more children. This means that the over-representation of children in our data is largely due to a relatively small number of families with a relatively large number of children.

definition that includes unemployed workers in three categories: A (job seekers with no job and actively seeking employment), B (job seekers with a reduced activity of 78 hours or less in the month, and actively seeking employment), and C (as in B but for with a reduced activity of 78 hours or more 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 ALB; 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 ALB. 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 nationwide ratio between the number of individuals in the labor force (31 million in 2023) and the number of households in the labor force (25 million); see here. This constant in the denominator has no impact at all on our estimates, since it affects all ALBs uniformly by construction.

[35] Figure 24 in Appendix A.1 complements these findings with additional graphs that focus on specific age sub-samples or report the percentage of individuals at every age who are the head of their own household. Restricting the population to the 60+ or to ages 0-59 yields similar results as in the overall sample, showing that the over-representation of children is not a mechanical artifact of the under-representation of retired adults. Almost no 0-18 year old is their own household head.

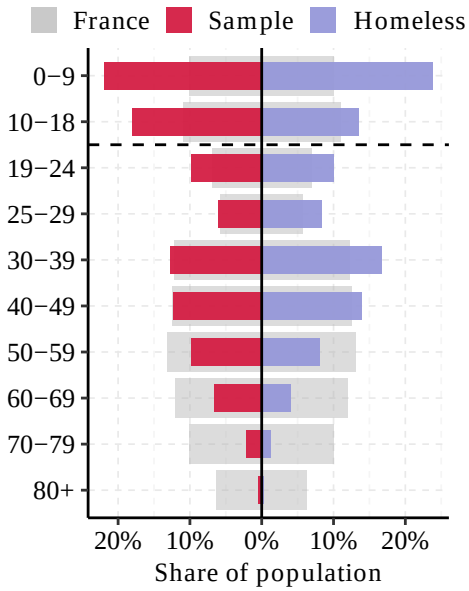
Table 1. Summary statistics for the resident: full sample and breakdown by housing status.

	RDC Resident Subsample								France[a]
	Full Sample		Private Rental		Social Housing		Housing Insecurity		
Variable	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean
Demographics									
Age	45.48	(14.46)	45.23	(14.66)	47.76	(13.83)	39.98	(13.73)	54.7
Family consumption units	1.57	(0.640)	1.56	(0.635)	1.61	(0.645)	1.49	(0.615)	1.51
Couple	0.333	(0.471)	0.345	(0.475)	0.331	(0.471)	0.308	(0.462)	0.590
Single man	0.235	(0.424)	0.245	(0.430)	0.176	(0.380)	0.331	(0.471)	
Single woman	0.432	(0.495)	0.410	(0.492)	0.493	(0.500)	0.361	(0.480)	
# children	0.972	(1.30)	0.947	(1.29)	1.05	(1.33)	0.887	(1.24)	1.035
# children aged 0–3	0.182	(0.450)	0.168	(0.430)	0.171	(0.435)	0.232	(0.499)	
# children aged 4–12	0.555	(0.927)	0.549	(0.918)	0.608	(0.954)	0.489	(0.873)	
# children aged 13+	0.235	(0.541)	0.230	(0.535)	0.267	(0.565)	0.165	(0.468)	
Disabled	0.085	(0.279)	0.092	(0.290)	0.096	(0.294)	0.043	(0.203)	0.041
Student	0.031	(0.172)	0.042	(0.201)	0.016	(0.126)	0.050	(0.218)	0.050
Retired / pre-retired	0.107	(0.309)	0.110	(0.313)	0.124	(0.330)	0.048	(0.213)	0.283
Finances (per CU)									
Work	0.107	(0.309)	0.123	(0.329)	0.103	(0.304)	0.067	(0.251)	0.530
Earnings	75.12	(206.72)	95.39	(235.66)	66.77	(191.08)	55.85	(170.89)	
Total income	637.76	(317.58)	718.50	(296.18)	708.99	(264.16)	396.21	(312.92)	2256.98
Transfers	431.00	(331.90)	472.35	(343.60)	503.07	(307.99)	268.85	(301.18)	188.74
Housing benefits	113.81	(107.29)	144.20	(109.95)	148.07	(91.13)	32.38	(82.63)	
Income w/o housing benefits	599.41	(310.01)	667.30	(297.49)	660.34	(266.23)	385.02	(301.64)	
Housing expenses	226.08	(282.85)	323.49	(269.14)	250.20	(336.58)	84.86	(142.06)	326.56
Expenses (incl. other regular)	300.23	(241.49)	402.62	(209.86)	343.63	(226.42)	112.66	(182.76)	
Income minus housing expenses	411.68		395.01		458.79		311.35		1930.42
Resources left for consumption	337.53	(273.26)	315.88	(269.72)	365.36	(269.62)	283.54	(258.42)	
Consumption according to RDC	54.50	(38.24)	53.09	(36.72)	57.35	(37.68)	52.39	(41.82)	
In debt	0.149	(0.356)	0.153	(0.360)	0.181	(0.385)	0.074	(0.262)	0.438
Debt repayment (for indebted)	114.98	(328.57)	120.77	(276.70)	97.24	(360.78)	116.32	(267.28)	
Survival in sample									
Goes to the charity next year	0.528	(0.499)	0.520	(0.500)	0.562	(0.496)	0.511	(0.500)	
Repeated spell (new spells in 2024)	0.117		0.118		0.147		0.082		
Local covariates (ALB level)									
Annual income per capita (in k€)	15.77	(3.79)	15.24	(3.33)	15.90	(3.91)	16.68	(4.29)	17.13
Unemployment (broad) rate (%)	19.64	(4.11)	20.08	(4.31)	19.61	(4.05)	18.98	(3.83)	18.29
Private rent (€/sqm)	13.47	(5.56)	12.42	(5.10)	13.79	(5.55)	15.02	(6.12)	14.48
Private rent (CAF, €/sqm)	9.87	(3.21)	9.22	(3.00)	10.06	(3.15)	10.81	(3.52)	10.54
Social rent (€/sqm)	5.64	(0.794)	5.49	(0.778)	5.71	(0.765)	5.85	(0.840)	5.75
Private rentals per k hh	67.28	(32.38)	63.31	(30.72)	68.57	(32.68)	70.57	(32.57)	66.78
Social housing units per k hh	136.41	(71.39)	113.29	(69.73)	152.39	(69.96)	145.67	(66.29)	130.69
Shelter capacity per k hh	6.86	(5.88)	5.41	(5.53)	7.39	(5.79)	8.50	(6.12)	7.26
Price index	109.98	(9.03)	109.46	(8.97)	110.40	(9.16)	111.45	(9.16)	109.36
Firm stock (per k hh)	131.27	(43.06)	129.17	(39.77)	130.28	(44.37)	139.32	(46.28)	142.23
Urbanization									
City center	0.514	(0.500)	0.506	(0.500)	0.529	(0.499)	0.524	(0.499)	0.317
Suburb	0.303	(0.459)	0.238	(0.426)	0.338	(0.473)	0.342	(0.474)	0.379
Isolated city	0.108	(0.311)	0.138	(0.345)	0.092	(0.289)	0.085	(0.278)	0.090
Rural area	0.075	(0.264)	0.118	(0.323)	0.041	(0.198)	0.049	(0.216)	0.214
Share of observations	100%		29.45%		43.43%		21.87%		

[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 ALB averages or postal code averages (for urbanization), weighted by population, between 2018 and 2023. Summary statistics for non-residents are shown in Table 16 of Appendix B.1.

Figure 8. Age distribution and family structure of children (sub-sample of residents).

(a) Age distribution (all)



(b) Children by family structure and age

		Sample		Homeless	
Age group		0–9	10–18	0–9	10–18
Couple	1 child	6.7%	5.8%	8.1%	5.2%
	2 children	16.7%	11.8%	18.3%	12.7%
	3+ children	38.5%	33.4%	31.6%	32.6%
Single mother	1 child	7.2%	10.3%	10.7%	9.1%
	2 children	11.7%	13.8%	13.0%	12.7%
	3+ children	16.2%	17.7%	14.9%	18.2%
Single father		2.8%	6.3%	3.0%	6.3%
No parent		0.1%	0.9%	0.3%	3.2%

Note: The corresponding results for non-resident households are reported in Appendix B, Figure 29.

Spell Duration (residents). Table 1 shows there is a fairly low "survival" rate – defined by the number of households in a given period who are still in the sample a year (i.e., two consecutive RDC campaigns) later.[36] On average, "only" about half (53%) of the current RDC recipients remain in the sample a year from the current period. That is, the median duration of a spell of food insecurity is about 1 year. The housing insecure are slightly more likely to exit, while social housing tenants are the most likely to remain at RDC, with a 56% survival rate after one year. In other words, food and housing insecurity are relatively *transient* states.

Concretely, how long is the average duration of food and housing insecurity spell? Because we do not observe RDC recipients after the winter 2025, the latest available campaign as of the writing of this paper, the longest spells are right-censored – that is, we do not observe the full spell of an individual who entered RDC in 2023, say, and is still present in 2025. To compute the distribution of spells, we thus proceed as follow. We track households who entered RDC between 2019 and 2021. Only a small fraction of them stay longer than 10 consecutive campaigns in the sample. For these households, we impute a spell duration of 10 campaigns, or 5 years. Doing so introduces only a minor downward bias to our estimated

[36]The definition we use here is different from the one we use for "exits" later in the paper. In the present paragraph, we count as an "exit next year" a household in period t (e.g., summer 2023) who no longer appears in the sample in the same season a year later, i.e., in period $t+2$ (summer 2024).

average duration. With this caveat in mind, we obtain that households stay in the sample for 3.10 campaigns on average (or approximately 18.6 months).[37] For older households (i.e., those whose head is above age 65), the corresponding average spell duration is 3.58 campaigns (21.5 months), and 2.44 campaigns (14.6 months) for those younger than 25.

In addition, Table 1 shows that repeated spells (i.e., households that exit the sample and return in a later period) are relatively rare: 11.74% of the spells started in 2024 (summer or winter campaigns) belong to households that had a previous spell between 2017 and 2023. This share varies with housing status at entry, from 14.74% for households in social housing to 8.2% for those in housing insecurity. The data also record the date of first contact with RDC, which we use to confirm our estimate of the occurrence of repeated spells. In 2024, all households in a repeated spell reported a prior contact with RDC, whereas only 1.9% of entrants that we classified as new spells had an earlier first contact date (usually before 2017, the first year of our panel). Using both measures, we can thus confidently argue that repeated spells represent between 11.7% and 13.7% of the 2024 spells.[38]

Next, Figure 9 complements these average statistics by showing the *distribution* of spell durations for households who entered RDC in 2019. Consistent with our previous findings, the left panel shows that about 40% of the households only spend one period at RDC (i.e., they leave within 4 months if the individual entered in a winter campaign or within 8 months if they entered in a summer campaign) The right panel shows that the fraction of short spells is especially high for younger households. We also find that only about 14% of the recipients remain in the sample at least 3 consecutive years (6 campaigns), and about 6% stay for 5 years (10 campaigns) or more. Note that these high exit rates should not overshadow the fact that more than 20,000 individuals are present in our sample for all 17 campaigns in a row (8 years).

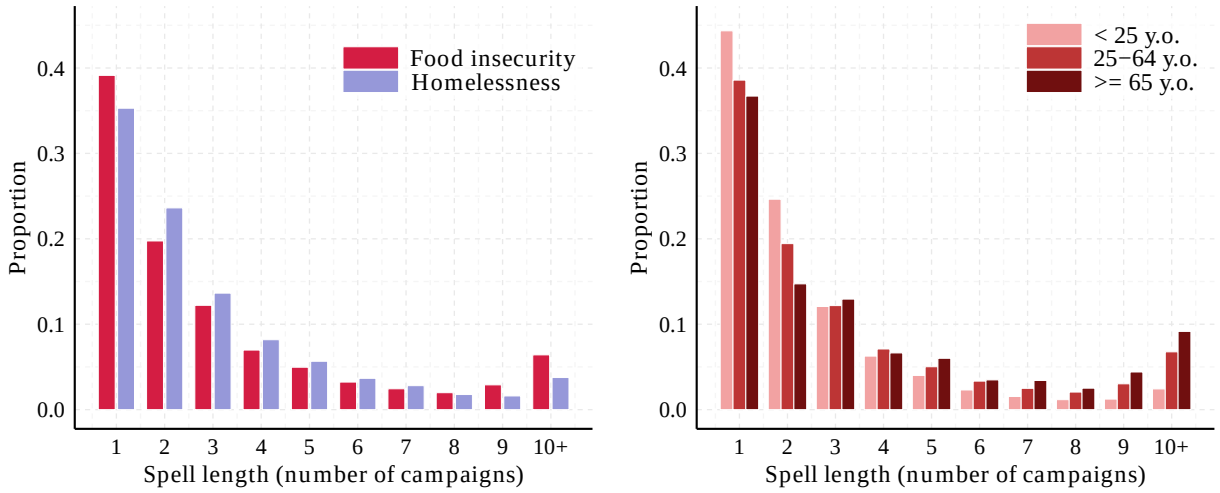
More generally, what can we say about the right tail of the distribution, i.e., the proportion of very long-term recipients? Unfortunately, we do not have data before the 2017 winter campaign. However, we have access to the yearly reports from the charity since 2009. For the winter 2012 and summer 2013 campaigns (henceforth "2012-13"), RDC reported the number of individuals whom they served, as well as the number of individuals who entered for the first time in that year. Moreover, our sample gives us the first entry date of each

[37] Recall that winter campaigns last 4 months and summer campaigns 8 months. We simplify this back-of-the-envelope calculation by assuming that each campaign spans 6 months on average. Our calculation yields an upper bound on the average duration of the spell by assuming that new recipients enter at the beginning and leave at the end of the campaign, i.e., that they spend the whole 6 months in food insecurity.

[38] Reassuringly, households report their date of first entry consistently: Only 0.7% give different first contact dates across campaigns, perhaps due to family changes.

individual at RDC. Therefore, we can estimate the probability of returning to the charity in the very long run, defined here as 5 to 10 years after the first entry. For the 432,000 first entrants in 2012-13, we find that only 3.64% of them (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).[39] Compared to the sample of all households (including all foreigners) over the same time period, these 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 on average for the household head), 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 housing insecurity: 49.5% vs. 32.8% in social housing, 28.2% vs. 25.1% in private housing, 9.5% vs. 14.6% in housing insecurity, and only 6.8% vs. 23.5% strict homeless. This suggests again that long-run housing insecurity is much less frequent than long-run food insecurity. Finally, in the sample of all households present at least once between the winter 2017 and the summer 2022, those who entered for the first time in 2012-13 are on average present in 4.46 campaigns (out of the 10 campaigns of these 5 years), while the average household is present for 2.47 campaigns.

Figure 9. Left panel: distribution of spells of food insecurity and homelessness. Right panel: distribution of spells of food insecurity by age group.



All of these results consistently show that we are very far from the naive and simplistic view of households that would remain "homeless for life". One final remark, though, on the

[39] 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.

interpretation of a household exit from the sample. Recall that exits can be due to various factors that we cannot directly observe – we do not know whether they exited because they found a job, and if so with what salary, because they prefer seeking help from another charity, or because they moved out of the country or passed away. The latter two explanations cannot account for the patterns we uncovered. Migration outside of France is unlikely for this subsample given that we are focusing on documented residents with access to welfare benefits (the results are unchanged by further restricting to French citizens), and deaths affect only a very small share of homeless individuals in our sample.[40] It is also possible, though difficult to quantify, that some recipients drop out of the sample even though they remain in extreme poverty, because they prefer to request assistance from another charity (or no charity at all). Note, however, that our high exit rates from homelessness are consistent with findings from the EU-SILC survey, in which households reporting a past episode of homelessness or severe housing precarity 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.[41] Furthermore, Figure 21 in the Appendix shows that the probability of re-applying to RDC in the next campaign is increasing in the fraction of time the household visited their drop-in center in the current period and close to 1 for those who collected food every week since their entry date. To the extent that this variable reflects the severity or the duration of their distress, we can argue that households who exit the sample are indeed those who no longer need food assistance, i.e., who "got back on their feet".

Finances (residents). We conclude this section by discussing the finances – income, expenses, rest-for-living, and within-charity consumption – of the residents in our sample.

[40] 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 housing insecurity situations) in our sample. For the U.S., Meyer et al. (2025b) and Christopher et al. (2025) find that homelessness is associated with higher mortality rates, about 3.5 times as high as those of the housed in the latter paper using large-scale administrative data. Using this estimate as a benchmark and the fact that the mortality rate in France for 45-year-olds (the average age in our sample) is below 0.2% per year (source here), we would obtain at most 1% of deaths among the homeless every year, far below their 50% exit rate from our sample.

[41] 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 finding 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%) of the observations – 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. Appendix A.3 provides similar estimates from other charities or statistical institutions. Allgood and Warren Jr (2003) also find that spells are generally short among a survey of roughly 4,200 U.S. individuals, with more than half lasting under three months.

Table 1 shows that total household income equals 638€ per CU on average, most of which consists of transfers (431€). The most important welfare benefit in France is the RSA, or "*revenu de solidarité active*", a monthly payment distributed to households with no labor income under conditions of age (recipients must be at least 25 years old, with exceptions for single parents with children) and residency (3 months for foreign EU citizens, 5 years otherwise).[42] Only 11% of the residents in our sample have at least one household member who is employed. Average labor earnings per CU in the sample are equal 75€ per month (in 2025 euros). Note that these values reflect a combination of extensive and intensive margins; we give the corresponding conditional figures in the Appendix and show that average labor earnings amount to about 400€ conditional on being in a household with at least one employed member. Recipients in housing insecurity are less likely to be employed (7%) and have lower income on average (396€), in part – but not only – because they do not receive housing subsidies.[43]

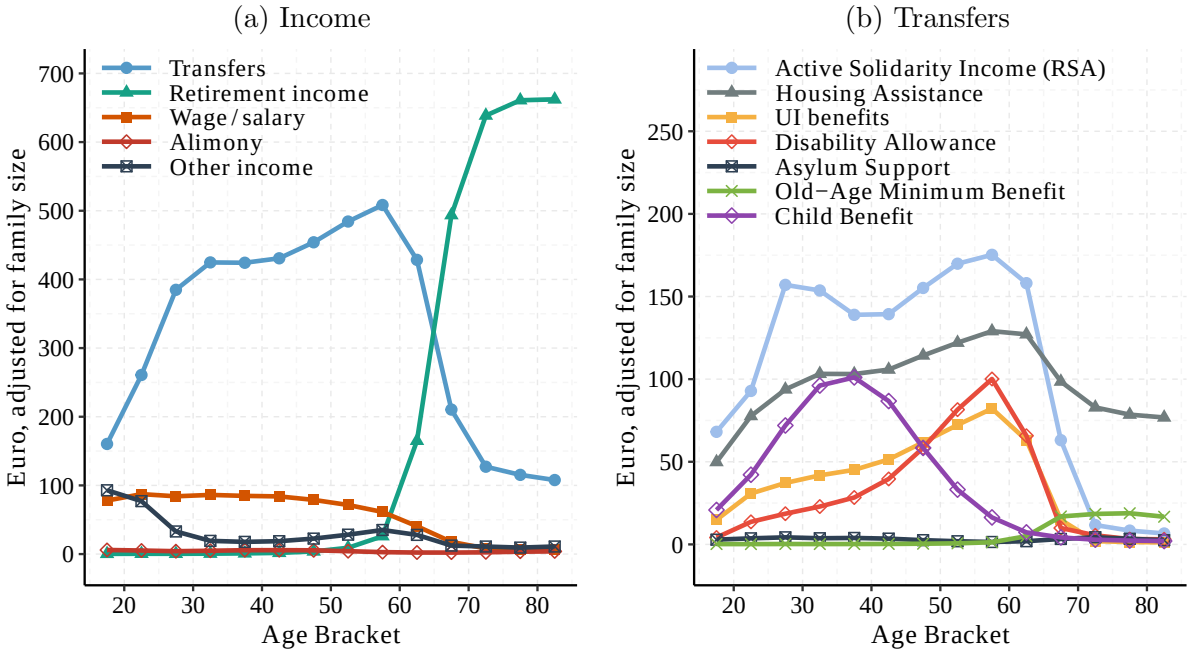
The left panel of Figure 10 gives a decomposition of the average monthly income along the life cycle into its main components: labor income, pensions, government transfers, alimony received, and other regular income. The right panel gives the decomposition of welfare benefits into its main components. The corresponding amounts conditional on receiving each payment and for sub-groups of the population are shown in Figures 25 and 26 in the Appendix.

The strikingly low employment rates and the minor importance of wage income, especially in comparison to the U.S. where there is a large number of "working poor", can be explained by the combinations of several channels. First, the French labor market is much more sclerotic than in the U.S.: The official (ILO) unemployment rate is above 7.5% in 2025 compared to 4.2% in the U.S., while the youth (below age 24) unemployment rate is close to 20%, thus making it difficult for a large share of the population to find a job. Second,

[42]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 is equal to zero. The RSA allowance amounts to about 650€ per month in 2025 for a single individual with no children, and generally around a similar amount per CU. The precise eligibility rules and amounts depend on several variables and can be computed here. Unlike a literal UBI, however, eligibility is subject to some conditions: In addition to the age and residency requirements mentioned in the text, eligibility depends on an assessment of the individual's "lifestyle", including the value of their real estate, vehicles, appliances, vacation, etc. 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. Further details are available here.

[43]For future reference, Table 1 also reports a counterfactual measure of income "net of housing benefits" that excludes housing subsidies (APL) and adjusts the level of the RSA transfer accordingly; this variable has the advantage of being exogenous to the choice of housing status of the household that we use later as an outcome of our empirical analysis.

Figure 10. Decomposition of average income (left) and transfers (right) over the life cycle



Note: These two plots display unconditional averages. Conditional counterparts, computed only among workers, disabled households, indebted households, and RSA recipients, are reported in Appendix A.1, Figures 25 and 26. The corresponding results for non-residents are reported in Appendix B.1.

a labor supply explanation is also possible, where the low employment rates partly reflect the relative generosity of welfare benefits. Third, and most importantly, there is an obvious selection bias: Households are likely to request food assistance, and hence be present in our sample, precisely after they lose their job ; this does not imply that they will remain permanently unemployed or out of the labor force and live off of welfare benefits – this is consistent with the fact that pensions of recipients above age 60 are on average so much higher than wages during working life (in particular, the minimum pension benefit is not binding for most retirees even though it is nominally higher than the RSA). This is because pensions reflect lifetime incomes, whereas current income flows in our population may be the temporary outcome of a particularly bad year.[44]

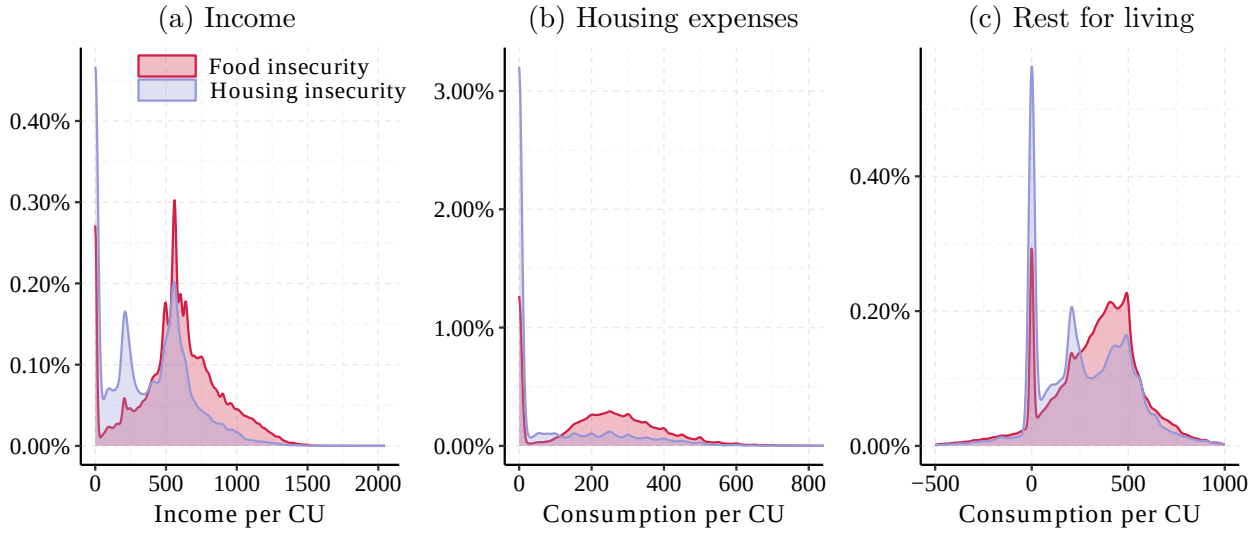
Consider now the expenses. Resident households spend on average 226€ in housing expenses (rent, mortgage, housing taxes, other housing expenses, and utilities). Rents amount to 45% of the income of private renters, and 40% of those of the social housing renters. Notice that housing-insecure households also have housing expenses that can be substantial: 85€ on average, or 20% of their income. These costs are those of occasionally sleeping in

[44] Another possible reason is that those receiving pensions today are baby-boomers who were more likely than the currently active cohorts to be employed during *their* working life several decades ago.

shelters, hotels, or even third party places, which are not necessarily free. Next, about 15% of RDC recipients (and 7% of the housing insecure) are in debt, and their average monthly debt service is 115€. Finally, *rest for living* – defined as the difference between total income and all recorded expenses (housing, debt payments, alimony) – amounts to 338€ on average. This level of resources left over for (non-housing) consumption is the variable that RDC uses to determine eligibility to their food assistance program. Social housing tenants have the highest resources left for consumption (365€) in spite of lower labor earnings, both because of higher average transfers and lower housing costs. Housing insecure households have the lowest rest for living (284€).[45]

Figure 11 complements these average levels of income and expenses by showing their *distributions*, both in the overall sample (red) and among the housing-insecure (blue). The left panel shows the distribution of income per CU; the middle panel shows that of housing expenses per CU; and the right panel shows that of non-housing consumption (rest for living) per CU. The income distribution has clear bunching masses at the RSA amount – around 600€ per CU though the exact value depends on the family structure – and at 0€. The latter mass point reflects a combination of non-eligibility to transfers (recall that the RSA is subject to an age requirement) and wait time or non-take-up of welfare benefits.

Figure 11. Left panel: Distributions of income per CU. Middle: Distribution of housing expenses per CU. Right panel: Distribution of non-housing consumption (rest for living) per CU.



Note: The corresponding results for nonresident households are reported in Appendix B, Figure 31.

[45]Interestingly, further restricting the sample to French citizens shows that households in housing insecurity receive slightly higher transfers (466€ on average) and, as a result, have an almost identical rest for living as the private tenants (338€ vs. 340€).

Taking Stock. Contrasting the distributions of income and rest for living illustrates a fundamental insight about the measurement of poverty. Some households in our sample appear, perhaps surprisingly, to have relatively high monthly incomes (inclusive of transfers): The 90^{th} percentile among resident RDC recipients is at 1,300€, and the 97.5^{th} percentile is slightly above 1,700€. By comparison, survey data such as the HFCS or EU-SILC places the 10^{th} percentile of the overall French income distribution at 1,100€, while the 25^{th} percentile is around 1,700€ (see Table 6 in the Appendix).[46] In other words, according to these data sets, the highest income in RDC is at a similar level as the 25^{th} percentile of the overall French distribution, and only 50% of the RDC recipients are located below the 5^{th} percentile. Given that our sample (including non-residents) contains less than 2% of the French population in a given year, these comparisons may suggest that our sample misses a very large share of the poor. Besides the significant and well-documented under-reporting of transfers in survey data,[47] one should view this comparison not as a flaw but as a major *strength* of our data set. Individuals in our sample should not be interpreted as necessarily the most *income*-poor in France, but as the *consumption*-poor, which we think is a far more relevant measure of poverty (see Han et al. (2022)). By definition, RDC recipients are the households who self-select into requesting food assistance from a charity. Hence, the outcomes we observe account for various observed and unobservable underlying factors that households are facing – such as the cost of living and aggregate economic shocks in the area where they live, their non-discretionary expenses, their support network (or lack thereof) and private insurance against economic hardships, etc. Such personal circumstances would be overlooked by restricting attention only to their financial resources. In other words, we believe our sample provides a more accurate picture of *actual* poverty than alternative data sets in practice.

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

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

3 Econometric Specifications

The remainder of the paper is devoted to understanding the determinants of extreme poverty. Specifically, our goal is quantify the factors – local economic conditions, policies, and individual characteristics – that explain entry into and exit from food and housing insecurity. In this section, we describe our methodology and econometric specifications. For conciseness, in this section only we refer to "homelessness" as either strict homelessness or broad housing insecurity (our empirical results in Section 4 study these sub-populations separately).

3.1 Entry Flows

We start by exploring the impact of local economic shocks on the probability of *entering* deep poverty. Because we do not observe individuals before they enter the sample nor the joint distribution of individual characteristics in the overall population of each location, we cannot evaluate the impact of individual characteristics on entry flows; we thus restrict attention to the impact of location characteristics.

We define the entry rate into homelessness (resp., food insecurity) in location (ALB) j and period t as the number of newly homeless (resp., in-sample) households, scaled by the total number of households in that location.[48] Denote these probabilities of entry into homelessness and the sample by E_{jt}^{homeless} and E_{jt}^{sample}, respectively, and let $\overline{E}^{\text{homeless}}, \overline{E}^{\text{sample}}$ denote their average over time and across ALBs.

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

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

where $\mathbf{X}_{jt}^{\text{local}}$ is a vector of local characteristics detailed 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. Our results, presented in Section 4, report the results of regression (1) weighted by the population of the local ALB.[49]

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

[49] By assigning greater weights to ALBs 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

Because the outcome is a count variable and many locations have 0 entries into homelessness, we alternatively estimate the relationship (1) using a Poisson model.

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 ALBs. More precisely, we define a location as ALB $\times$ 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 campaign of our sample to the previous winter campaign, and similarly for summer campaigns.

The vector of local characteristics includes the share of retired households, the unemployment rate, the average income, the food price level (at the département level), private rents per square meter both for units currently occupied by welfare recipients ("CAF") and for newly listed vacancies, the number of private rental listings, social housing rents per square meter, the stock of social housing units, the capacity of homeless shelters, the stock of firms per capita, the creation of sole-proprietor and other firms, the cessation of firms, the shares of various industries (manufacturing, construction, social services, etc.), and average temperature and rainfall in the current season. We also add the following interaction variables: unemployment times private rents and unemployment times social housing stock. These interaction terms capture joint, nonlinear effects: whether places with higher rents are more sensitive to changes in the unemployment rate, or whether a larger stock of social housing provides the living basin with insurance against unemployment shocks. Finally, we also control for the number of RDC drop-in centers per household in every location.

3.2 Exit Flows

Next, we study the determinants of the probability of exiting homelessness or food insecurity. Because, in contrast to the previous subsection, we observe households before they exit our sample, we can run regressions at the individual level and estimate the impact of both individual characteristics and local economic shocks on the exit flows. (For robustness, we also run the regressions at the location level in Appendix A.2.1.

Exit: Definition. Throughout the paper we say that a household "exits" the sample if they are present in the sample in period t (say, summer 2023), and absent for at least one full year thereafter (i.e., in periods $t+1$ and $t+2$, winter 2023 and summer 2024). Using these

better approximates the individual probability of entry than the unweighted specification that treats each ALB identically. For robustness, Appendix A.2.1 also reports the results of the unweighted OLS regressions.

particular timing conventions (rather than, for instance, defining an exit as being absent in the subsequent campaign) is innocuous for our main results but allows us to work at the campaign frequency (biannually) without creating spurious exits due to seasonal changes in the acceptance threshold or to closures of some RDC drop-in centers in summer campaigns.

Exit Model. 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 $\eta \in \{\text{homeless}, \text{sample}\}$,

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

where j is the location (ALB $\times$ season) in which individual i lives in period t. Note that the subscript $t+1$ in $\mathbf{X}_{j,t+1}^{\text{local}}$ contains a slight abuse of notation: For the local characteristics that are only available at yearly frequency, we use their value in the same year $(t+1)$ as explanatory variable for the probability of exiting in the winter (November) campaign, but their value in the previous year (t) as explanatory variable for the probability of exiting in the summer (March) campaign.[50]

In addition to the same location characteristics as in the entry model (1) collected in the vector $\mathbf{X}_{j,t+1}^{\text{local}}$, equation (2) also contains (a third-degree polynomial $\psi(\cdot)$ in) the variable $\widehat{P}^{\text{sample}}_{\underline{j}(it),\underline{t}(it)}$, which denotes the probability of entry into the sample (estimated from the entry regression model (1)) in the location $\underline{j}$ and at the time $\underline{t}$ where the individual started their current spell. Including (a flexible function of) the household's predicted probability of entry at the start of their current spell controls for potential selection into the sample based on the characteristics of the location. Intuitively, it verifies whether locations where entry is more likely also have systematically different exit rates.

The vector of individual characteristics $\mathbf{X}_{it}^{\text{indiv}}$ includes demographic variables (age, gender, marital status, number and age of children, citizenship, education, disability, housing status, frequency of visits at RDC in the past year), household financial variables (income, housing subsidies, housing expenditure, indebtedness dummy, RSA take-up), and duration-dependence variables (repeated spell dummy, duration of the current spell). 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

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

exited the sample.

RDC Usage Index. While our definition of an exit is at the extensive-margin level (we only observe that households have left at the beginning of the next campaign, potentially several months after they actually stopped visiting their RDC drop-in center), we can also construct an intensive-margin variable that we call "RDC usage index", U_{it}. This index, which takes values between 0 and 1, is defined as the number of weeks that a household visits their drop-in center during the campaign, divided by the number of weeks between their entry date and the end of the campaign. This gives us the fraction of time that they visit RDC to collect food since they first entered. (Unfortunately, we do not observe the date of their last visit, which prevents us from measuring the intensity of their needs.) We can then run the following regression in each subsample (homeless, sample):

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

where the right-hand side variables are analogous to those in equation (2).

Technical Remark: Survival Model. Because we include duration dummies as covariates, the model (2) 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 a household is present in the first period of our sample, i.e. winter 2017, we cannot tell when the spell started and we set its duration to unknown).[51] Right censoring concerns are mechanically handled by this discrete-time survival model, because it proceeds period by period and, in the last period of the data, the dependent variable (the next period indicator $\mathbb{I}^{\eta}_{i,t+1}$) is not observed. Since we have many observations and only a few discrete duration possibilities, we prefer to run this discrete-choice survival model rather than a Cox survival model, since the former is more natural and flexible.[52]

Correcting for Sample Selection. Even though we argued above that this is unlikely, it remains possible that RDC recipients may not be representative of overall food and housing

[51] The first contact date discussed earlier cannot be used to define a spell because it does not reveal exits and re-entries (e.g., a household could enter in 1998, exit in 2000, and re-enter in 2016).

[52] An alternative to our simple linear probability model is to use a complementary log log (clog-log) distribution for the error term. This would make our discrete-choice survival model the discrete-time (or 'grouped-time') equivalent of a (continuous-time) Cox proportional hazard model (Meyer, 1990). The results we obtained with the clog-log model are very similar to those using our linear probability model. We thus only report the latter as the coefficients are easier to interpret.

insecurity if the sample suffers from a selection bias. For instance, households who are more likely to apply for food assistance at RDC may have unobserved personal characteristics that also make them more (or less) likely to apply for jobs and thus exit the sample. To address this issue, note that much unobserved heterogeneity is already captured by controlling for many observable characteristics in equation (2), including the household's housing expenditures, as well as their predicted probability of entry at the start of their current spell $\widehat{P}^{\text{sample}}_{\underline{j}(it)\,\underline{t}(it)}$. The latter correction is in the spirit of semi-parametric sample selection models as in, e.g., Newey (2009), and controls for the fact that households who entered RDC in a a more "favorable" environment (i.e., where entry was more likely) may have different unobserved characteristics from those who entered in places and at times where the probability of doing so was lower.[53,54] Because of all these controls, we interpret the effect of the spell duration covariate in (2) as a scale-dependence effect of duration. Furthermore, adding random intercepts to the regression does not substantially alter our results in Section 4. That said, it remains of course technically possible that individuals in our sample are selected on unobservable characteristics that we cannot control for. With a limited number of repeated spells, it is hard to identify such unobserved types, though it will become feasible in the future with additional time periods.

4 Determinants of Food and Housing Insecurity

This section presents our estimates of the coefficients of regressions (1) and (2). We then use these estimates to elicit the role played by macroeconomic shocks in the staggering rise in homelessness and food insecurity in France between 2018 and 2025. We mainly focus on the sub-sample of residents in the main text. The results for non-residents are gathered in Appendix B.2.

[53] We can only include location-level covariates to control for the probability of entry. Ideally, we would need to observe and include all individual covariates. Nevertheless, we still think our approach controls for selection on individual characteristics to some extent: When the probability of entering RDC increases because a new drop-in center opens (our main excluded variable), more households are selected into the sample, which therefore reflects a different pool of individual characteristics.

[54] 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. The effect of the probability of entry is identified separately from those of other covariates thanks to a timing assumption. Specifically, we assume that a covariate evaluated at time t significantly impacts the probability that an individual applies for RDC support in that period and location; but conditional on the level of the covariate in the *next* period $t+1$, its value at time t does not impact the probability that an individual exits the sample in the *next* period $t+1$.

Identification Strategy. Recall from our discussion in Section 3 that, since our regressions contains location (ALB) and time (season-year) fixed effects, our identification of the economic determinants of inflows and outflows relies on the *differential evolution* of local economic characteristics *across locations*. Figure 12 illustrates this variation for private rents and the unemployment rate over the 2018-2023 period. Suppose for instance that we observe higher rates of rent inflation from period t to $t+1$ in Brittany relative to Paris. If, all else equal, Brittany also had a higher percentage increase in RDC recipients than Paris between these two dates, we conclude that private rents have a positive effect on food insecurity and we can thus compute the corresponding elasticity.

Baseline Entry and Exit Rates. For reference, we report the average entry and exit flows. Nationwide, in each campaign, there are on average 2.11 entries into food insecurity, and 0.277 entries into homelessness, per 1,000 households. Since some of our regressions are at the ALB-level, we also report the unweighted averages across ALB locations. There are on average 2.12 entries into food insecurity, and 0.17 entries into homelessness, per 1,000 households, across ALBs and campaigns. Note that the the latter is much lower than the nationwide average, since many ALBs have zero entries into homelessness. Finally, about 38.8% of the local homeless population exits homelessness in each campaign on average across ALBs, while 31.7% exit food insecurity.

4.1 Determinants of Entry Flows

Table 2 gives the results of regression (1) estimated using (population-weighted) OLS, that is, the impact of local economic characteristics on the entry rates into (strict) homelessness, housing insecurity, and food insecurity. Appendix A.2.1 contains the results using a Poisson estimation.[55]

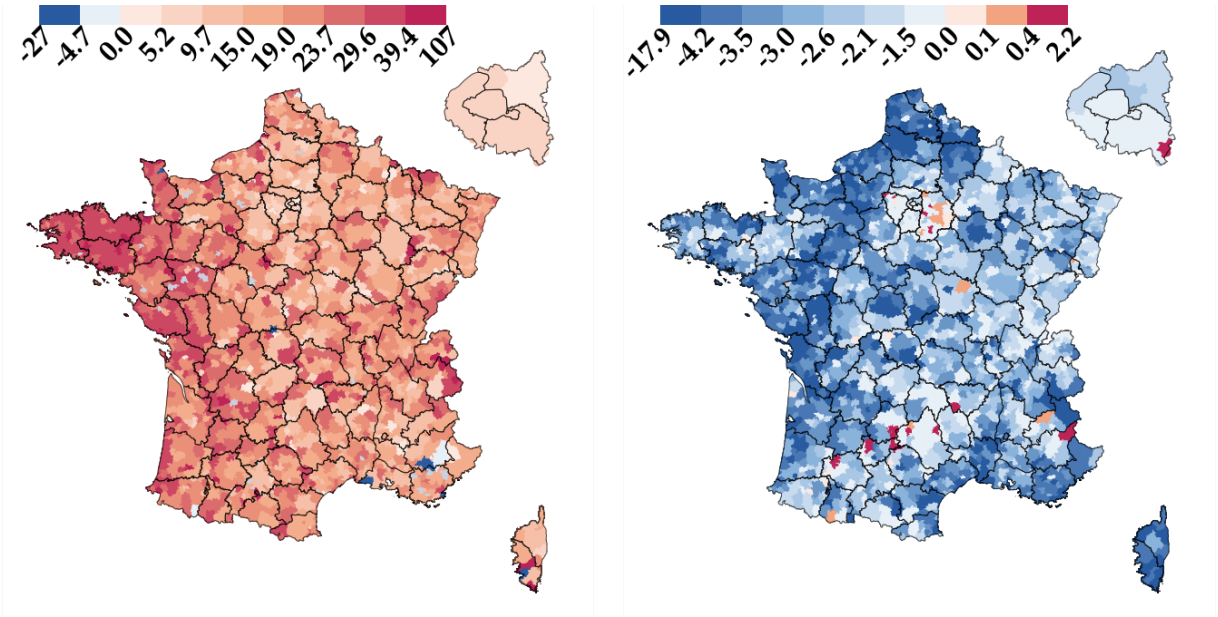
Economic Activity. First, Table 2 shows that the local labor market and broader economic conditions have a very large impact on inflows into homelessness and food insecurity. Specifically, a 10% increase in the local unemployment rate[56] raises the entry rate into homelessness (resp., housing insecurity, food insecurity) by 10.9% (resp., 10.2%, and 13.1%). That is, a shock to the unemployment rate – one of the most volatile macroeconomic time series –

[55]The results are consistent with those obtained for French citizens rather than residents (see Appendix A.2.3). They are also very similar using cantons rather than ALBs as the geographical unit of aggregation, and year-to-year transitions instead of wave-to-wave transitions. We do not report these tables for reasons of space, but they are available upon request.

[56]This corresponds to a 2 percentage point increase from a baseline 20%, see Table 1.

Figure 12. Evolution of selected variables at the local level (ALB-level) between 2018 and 2023.

(a) Private rent inflation (2018-23) (b) Unemployment pp difference (2018-23)



Note: Paris and its neighboring suburbs are expanded on the top right of each map. Recall that Figures 5 and 6 showed the spatial variation in the *levels* of private rents and unemployment. Here we show the percent *changes* in these variables between 2018 and 2023.

passes through one-for-one to extreme poverty. To give a concrete example, consider the Jura *département*, a rural area with an overall population of about 120,000, where France's best cheese (Comté) is produced.[57] Suppose that its unemployment rate rises by 25%, roughly corresponding to its change during the Great Recession.[58] This would increase the flow into housing insecurity among resident households by 27.1%, from a baseline of 300 in 2025. In other words, this would cause 81 additional households to fall into housing insecurity.

Next, higher GDP per capita, proxied by the average local revenue, affects the entry flows negatively with elasticities ranging from -0.6 for food insecurity to -1.0 for homelessness. Perhaps surprisingly, the elasticities of inflows into food and housing insecurity with respect to food inflation are not statistically significant (though the point estimate is large for the inflow into homelessness). This is because most of the variation in food prices is absorbed by the time and location fixed effects, i.e., food inflation essentially followed a common nationwide trend.[59]

[57]Some of the coauthors of this paper strongly disagree with this statement and would have rather used the département of Orne, where Camembert is produced, as our leading example.

[58]The unemployment rate went from 6.4% in 2008:Q4 to 8.2% in 2009:Q4, a 28% increase. Source here. Using our broader definition of unemployment yields a similar percentage change.

[59]Regressing our department-level food inflation variable on département and time fixed effects gives an

Table 2. Determinants of Entry Rates: Effects of Local Covariates (Weighted TWFE OLS, ALB-level)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Log households	−2.358***	(0.872)	−0.375	(0.545)	1.554**	(0.690)
N RDC centers (per k hh)	1.254**	(0.598)	2.623***	(0.388)	4.966***	(0.521)
Log private rent	1.822***	(0.443)	0.459**	(0.233)	0.164	(0.182)
Log private listings (per k hh)	0.136	(0.177)	0.069	(0.092)	0.092*	(0.051)
Log private rent (CAF)	—	—	—	—	0.870***	(0.331)
Log private housing stock (CAF)	−0.557	(0.391)	−0.305	(0.238)	−0.195	(0.165)
Log social rent	−0.775**	(0.394)	−0.126	(0.232)	−0.011	(0.226)
Log social housing stock (per k hh)	−0.808***	(0.205)	−0.240*	(0.138)	0.171	(0.137)
Shelter capacity (per k hh)	−0.047***	(0.014)	−0.016*	(0.009)	0.005	(0.012)
Log unemployment	1.085***	(0.312)	1.019***	(0.220)	1.314***	(0.316)
Log food price index	0.324	(1.046)	−0.122	(0.661)	0.091	(0.642)
Log local revenue	−1.038**	(0.519)	−0.757**	(0.319)	−0.564***	(0.197)
Log firm creation (sole propr.)	0.487***	(0.107)	0.145**	(0.064)	−0.112	(0.074)
Log firm creation (other)	−0.074	(0.059)	0.009	(0.038)	0.019	(0.037)
Log firm closures (per k hh)	0.204	(0.135)	0.105	(0.074)	0.007	(0.050)
Log firm stock (per k hh)	−2.807***	(0.457)	−1.970***	(0.313)	−0.435	(0.322)
Share manuf., mining & related	5.758**	(2.891)	0.430	(1.730)	−2.495*	(1.496)
Share construction	0.799	(1.945)	1.436	(1.233)	0.675	(1.718)
Share wholesale, retail & food	−0.014	(1.882)	0.169	(1.013)	−0.854	(1.014)
Share public admin. & health	−1.762	(1.770)	−0.896	(1.173)	2.638**	(1.159)
Log avg. temp. × Winter	−2.143**	(0.877)	0.080	(0.519)	1.098**	(0.521)
Log avg. temp. × Summer	0.042	(2.290)	1.851	(1.567)	0.038	(1.176)
Log rain × Winter	−0.068	(0.088)	−0.016	(0.053)	0.051	(0.059)
Log rain × Summer	0.083	(0.076)	0.067	(0.050)	−0.006	(0.043)
FE: area × period	Yes		Yes		Yes	
Observations	17,700		17,770		18,171	
Squared Cor.	0.618		0.646		0.767	

[a] Clustered (area_FE) standard errors in parentheses. Signif. codes: *: 0.10, **: 0.05, ***: 0.01.
Note: Corresponding results for non-resident households are reported in Appendix B.2, Table 17.

Housing Market. 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 for units currently occupied by welfare benefit recipients (CAF) and another for 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.[60] 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 new leases should be

R^2 of 0.96.

[60] Source here.

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 13.5€ per square meter on average, see Table 1) raises the entry rate into homelessness (resp., housing insecurity) by 18.2% (resp., 4.6%), 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 8.7%.[61] On the other hand, active housing policies seem to be effective at reducing flows into housing insecurity: Raising the stock of social housing units by 10% results in a 8.1% (resp., 2.4%) reduction in the entry rate into strict (resp., broad) homelessness. Controlling for the stock of social housing, their rents do not have a significant effect on entry flows into food insecurity and broad housing insecurity (though they do significantly affect homelessness).[62] This absence of price signal for food- and housing-insecure households may be due to a rationed market, as getting access to social housing units (which are in short supply) can involve long wait times. This would suggest that the main policy margin to prevent housing insecurity would be to raise their quantity (or reducing the demand by better targeting the populations in need) rather than further subsidizing prices.

Industrial Composition. 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 strict (resp., broad) homelessness by a staggering 28% (resp., 10%). Note that higher rates of creation of new sole-proprietorship firms are mildly positively associated with entry into housing insecurity, which 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 homelessness is larger in areas with higher prevalence of firms that are large providers of low-skill jobs such as manufacturing. The presence of public administration, education, health, and social services seems to also reduce (though insignificantly so) 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.

[61] 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.

[62] The surprising sign of this relationship may be due to migration decisions, if homeless individuals, who are more mobile than current renters, choose to move to locations where rents are lower or more heavily subsidized.

Other Local Variables. The number of RDC drop-in centers in an ALB has a large and significant positive impact on entry into the sample. Climate variables play a role: Colder winter temperatures strongly raise entry into homelessness, possibly capturing the effect of higher heating costs.

Interaction Terms. Last, we run separate regressions with the following interaction terms between unemployment, private rents, and the social housing stock. The results are shown in Table 3.[63] We find that the impact of unemployment shocks on inflows into homelessness is amplified in places where rents are higher, and vice versa. Thus, housing inflation and unemployment shocks compound one another. Furthermore, housing insecurity is less sensitive to unemployment shocks in places that have more social housing units. That is, social housing seems to act as efficient insurance against recessions.[64]

Table 3. Determinants of Entry Rates: Main Effects and Interaction Terms (Weighted TWFE OLS, ALB-level)

	Homelessness		Housing instability		Food Insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Main effects (interacted variables)						
Log unemployment	−7.857***	(1.941)	−0.592	(1.532)	0.270	(0.859)
Log private rent	8.927***	(1.470)	−0.737	(0.917)	−5.714***	(0.911)
Log private rent (CAF)	—	—	—	—	8.203***	(1.454)
Log social housing stock (per k hh)	−1.257***	(0.470)	−0.790**	(0.313)	0.230	(0.346)
Interaction terms						
log(private rent) × log(unemp)	4.772***	(0.840)	−0.518	(0.516)	−3.378***	(0.521)
log(private rent (CAF)) × log(unemp)	—	—	—	—	4.130***	(0.744)
log(social stock) × log(unemp)	−0.645***	(0.227)	−0.415***	(0.151)	0.069	(0.166)
FE: area × period	Yes		Yes		Yes	
Observations	17,700		17,770		18,171	
Squared Cor.	0.625		0.646		0.767	

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

[63] 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.

[64] The negative coefficient on unemployment in the homelessness regression does not imply that unemployment reduces homelessness. The relevant marginal effect is $(\beta_{\text{unemp}} + \beta_{\text{unemp}\times\text{private}} \log(\text{private rent}) + \beta_{\text{unemp}\times\text{social}} \log(\text{social stock}))$, which is positive when evaluated at the sample means. The opposite signs for the private rent indices may reflect a real difference between actual housing costs (CAF rents) and broader market pressure (advertised rents), although the two are correlated enough that this result should be interpreted with caution. CAF rents are also the only private rent variable that is significant without interactions, and using this variable alone yields a positive interaction term that suggests an amplification of the effects of unemployment.

Non-Residents. Interestingly, Appendix B.2 shows that the results are qualitatively similar for non-residents, *except* for the unemployment rate which – perhaps unsurprisingly – does not appear to affect their propensity to enter food or housing insecurity.

Taking Stock. We have shown that locations that are richer on average, have tighter labor markets, lower rents, and larger shocks of firms and social housing are those where, everything else being equal, the likelihood of entering homelessness is lower. The corresponding elasticity estimates are large and significant – around 1 for both unemployment and rents. While the *signs* of our coefficient estimates are not surprising (which is reassuring!), the key novelty of our analysis consists of quantifying the *size* of these effects. We next turn to the impact of macroeconomic shocks and individual characteristics on the probability of *exiting* deep poverty.

4.2 Determinants of Exit Flows

We now focus on the determinants of exit rates from homelessness, housing insecurity, and food insecurity. Table 4 gives the results of the household-level regression (2). For robustness and comparison with the entry rate elasticities, Table 8 in Appendix A.2.1 reports the estimates obtained from ALB-level exit regressions, Tables 9 reports those obtained using Poisson regressions, and Table 10 gives the estimates of the usage-index regression (3). It also holds in the regression of the usage index as the outcome variable, our intensive-margin measure of exits (Table 10).[65]

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 propensity to exit either homelessness, housing insecurity, or food insecurity, with the exception of the industry composition of a living basin. Almost all of the estimated coefficients are both statistically insignificant and economically small – an order of magnitude smaller than those estimated in the entry regressions – or not robust. This insight holds all of the specifications that we have implemented. It holds both in the household-level regression (Table 4) and in the ALB-level regression (Table 8 and 9), confirming that the stark difference with the entry-rate elasticities we estimated above is not an artifact of the different level aggregation.

[65]Recall that the usage index is not a measure of the *intensity* of usage, but of the fraction of time a household visited their drop-in center during the campaign. If this index is low, they either exited soon after entering or collected food very infrequently. If the index is high, they went regularly to their drop-in center during the entire campaign.

Table 4. Determinants of Exit Rates: Household-level Regressions (TWFE OLS, ALB-level)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Local covariates						
Log private rent	0.220**	(0.100)	0.091	(0.060)	0.054	(0.033)
Log # private listings (per k hh)	0.008	(0.039)	0.027	(0.024)	0.022*	(0.013)
Log private rent (CAF)	—	—	—	—	−0.024	(0.067)
Log private housing stock (CAF)	0.131	(0.098)	0.040	(0.058)	−0.027	(0.034)
Log social rent	−0.175	(0.198)	−0.059	(0.104)	0.003	(0.049)
Log social housing stock (per k hh)	−0.046	(0.125)	−0.048	(0.066)	−0.026	(0.035)
Shelter capacity (per k hh)	0.001	(0.003)	−0.001	(0.002)	0.000	(0.002)
Log unemployment	−0.098	(0.098)	−0.158**	(0.065)	−0.019	(0.043)
Log food price index	−0.101	(0.274)	−0.062	(0.185)	−0.015	(0.108)
Log local revenue	0.055	(0.178)	−0.069	(0.112)	0.019	(0.063)
Log firm creation (sole propr.)	0.004	(0.041)	0.011	(0.024)	0.016	(0.014)
Log firm creation (other)	−0.060**	(0.027)	−0.019	(0.015)	−0.004	(0.008)
Log firm closures (per k hh)	−0.021	(0.020)	−0.002	(0.013)	−0.005	(0.009)
Log firm stock (per k hh)	0.176	(0.193)	0.012	(0.109)	0.057	(0.073)
Share manuf., mining & related	0.200	(0.988)	0.991*	(0.540)	0.478	(0.291)
Share construction	0.886	(0.896)	0.422	(0.498)	0.535*	(0.278)
Share wholesale, retail & food	0.747	(0.524)	0.368	(0.323)	0.351*	(0.200)
Share public admin. & health	2.008***	(0.767)	0.628	(0.443)	0.386	(0.256)
Individual covariates						
Age + Income + # children	*see text and Figure 14.*					
Duration dependence	*see text and Figure 15 (for food insecurity).*					
Not first spell	0.039***	(0.007)	0.005	(0.004)	−0.014***	(0.002)
Disabled	0.045***	(0.008)	0.015***	(0.006)	0.013***	(0.002)
In debt	−0.014*	(0.008)	−0.024***	(0.005)	−0.032***	(0.002)
Single man (ref: couple)	0.059***	(0.005)	0.028***	(0.004)	0.015***	(0.002)
Single woman (ref: couple)	0.041***	(0.004)	0.019***	(0.003)	0.002	(0.002)
N children aged 0–3 (ref: none)	−0.035***	(0.003)	−0.031***	(0.003)	−0.035***	(0.002)
Nationality: EU (ref: French)	−0.079***	(0.009)	−0.073***	(0.006)	−0.032***	(0.003)
Nationality: Other (ref: French)	−0.155***	(0.006)	−0.153***	(0.005)	−0.085***	(0.003)
Education: N1 (ref: N0)	0.023**	(0.009)	0.018**	(0.007)	0.009**	(0.004)
Education: N3	0.043***	(0.008)	0.026***	(0.007)	0.014***	(0.004)
Education: N7	0.060***	(0.018)	0.047***	(0.014)	0.029***	(0.009)
Rural (ref: city center)	−0.057***	(0.015)	−0.043***	(0.007)	−0.015***	(0.004)
Housing expenditure (CU): €1–100	0.005	(0.006)	0.007	(0.004)	−0.033***	(0.004)
Housing expenditure (CU): €100–200	0.011*	(0.006)	0.000	(0.004)	−0.087***	(0.004)
Housing expenditure (CU): €200–300	−0.049***	(0.008)	−0.044***	(0.006)	−0.129***	(0.004)
Housing expenditure (CU): €300–400	−0.091***	(0.009)	−0.080***	(0.007)	−0.161***	(0.004)
Housing expenditure (CU): €400–500	−0.131***	(0.016)	−0.113***	(0.012)	−0.187***	(0.006)
Housing expenditure (CU): €500–600	−0.106***	(0.040)	−0.110***	(0.030)	−0.210***	(0.008)
Housing expenditure (CU): €600+	−0.175***	(0.028)	−0.150***	(0.020)	−0.220***	(0.009)
FE: area × campaign season	Yes		Yes		Yes	
FE: year-campaign	Yes		Yes		Yes	
Selection control (poly.)	Yes		Yes		Yes	
Observations	169,527		341,571		1,405,610	
Within R^2 (R^2)	0.071 (0.117)		0.059 (0.097)		0.045 (0.070)	

[a] Standard errors clustered by area × campaign season in parentheses. Signif. codes: *: 0.10, **: 0.05, ***: 0.01.

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

Note: Corresponding results for non-resident households are reported in Appendix B.2, Table 4.

At first sight, a few location-level variables do seem to have a (marginally) significant impact on exit flows. Consider first the local unemployment rate: It reduces the probability of exiting housing instability (though it has no impact on either homelessness or food insecurity). Even so, the corresponding point estimate is an order of magnitude smaller than that obtained in the entry regressions of Section 4.1.[66] In other words, rising unemployment drives people into food and housing insecurity at much higher rates than falling unemployment lifts them out of these situations. Similarly, private rents also appear to have a mildly significant coefficient on exit flows from homelessness. Yet their sign is the *opposite* of what one would have expected: If anything, higher rents tend to raise exit rates for homeless households. We speculate that the counterintuitive sign of this relationship, which appears to be robust across specifications, reflects migration out of the ALB, if higher rents push homeless households – who are more mobile than renters – to relocate to more affordable locations. In any case, the magnitude of this effect is again economically very small.[67] Finally, all of the other local covariates discussed in the previous section are both extremely small and statistically insignificant, with the notable exception (in some of the specifications) of the shares of manufacturing, construction, wholesale/retail/food, and public administration in the industrial composition of the living basin – all of which help exiting poverty.

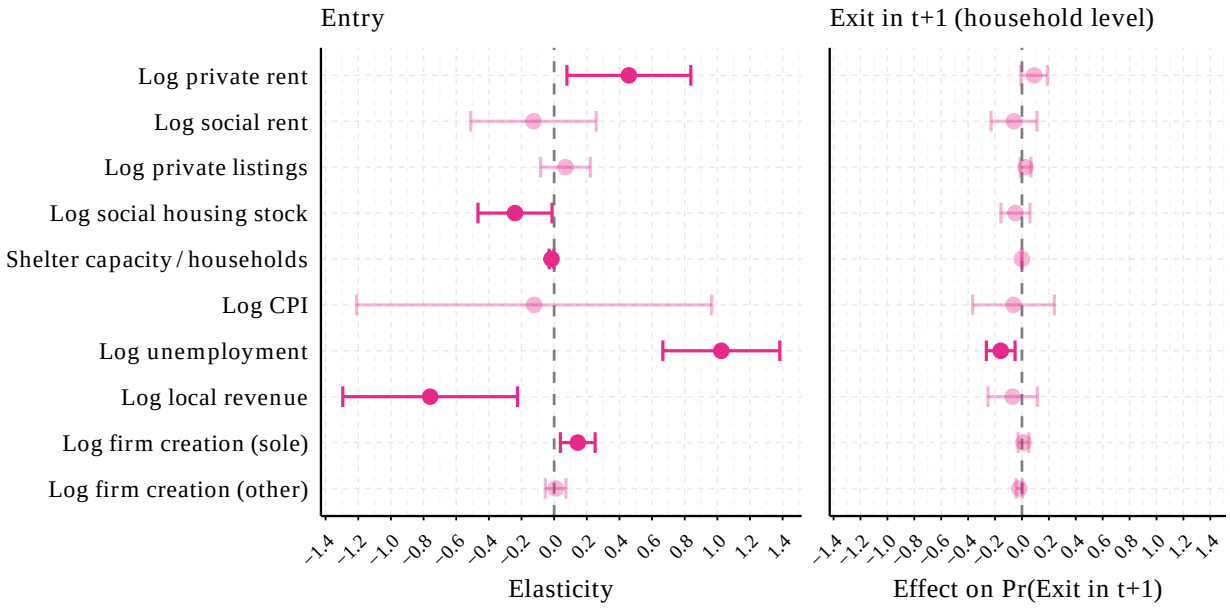
Figure 13 shows these results graphically for the case of housing instability. The exit rate elasticities are clearly negligible relative to their counterparts on the entry margin.

Individual Covariates. In contrast to the local economic conditions, individual or household covariates (unsurprisingly) play a very important role in explaining exit flows from extreme poverty. Consider first the demographic variables in Table 4 and Figures 14-15. Age is a very strong predictor of exiting: The older the individual, the less likely they are to exit both food and housing insecurity. Recipients who are 50 or older have more than a 15 percentage point lower probability of exiting food or housing insecurity in the upcoming year relative to 20-year old peers (recall that the average exit rates are around 50% overall). Single men and women are more likely than couples to exit homelessness and, to a lesser extent, overall housing or food insecurity. The effect of children varies with their age. Having a child

[66] Translating the semi-elasticities into elasticity coefficients comparable to the entry elasticity counterparts from Table 2 requires dividing these estimates by the average exit rates from homelessness, housing 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 4.3.

[67] One may think that the lack of effect of private rents on exit flows is due to the fact that the regressions control for household-level variables that include housing expenditures. However, Table 8 in Appendix A.2.1 shows that the same result holds in the location-level regressions.

Figure 13. Entry and exit rate elasticities: Housing insecurity



Note: The reported intervals are the 90% confidence interval.

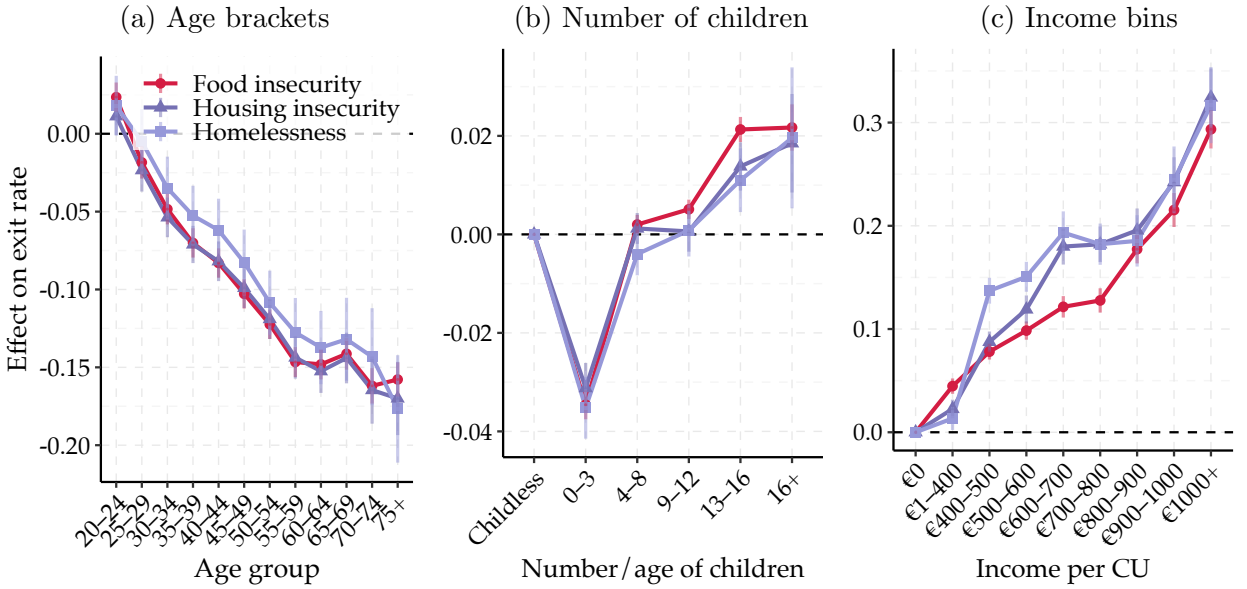
younger than 3 years old slightly reduces the odds of exiting both food and housing insecurity, likely due to the higher associated expenses. However, older children, and especially teenagers, have the opposite effect – perhaps reflecting in part a higher likelihood of being granted access to social housing. Disabled individuals are slightly more likely to exit food and housing insecurity, presumably due to their eligibility to benefits and potential priority access to social housing. Citizenship plays an important role: Even in this subsample of residents, immigrants – and especially non-EU citizens – have a much lower probability of exiting. Finally, exits from housing insecurity are monotonically increasing with education.

Consider next the financial variables. Figure 14 shows that exit rates are monotonically and strongly increasing in income (including transfers): The higher the per-CU resources of a household, the more likely they are to exit food or housing insecurity in the following period. Specifically, having an income of 600–700€ per CU per month, i.e., around the RSA allowance, raises the exit rate from food insecurity by more than 10 percentage points, and the exit rates from homelessness by 20 percentage points, relative to those who declare having no income.[68] Note that this gap could result from the direct impact of higher resources, or reflect a selection effect based on unobserved individual characteristics – such as better

[68]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), or those who are eligible but have not yet applied or received transfers.

access to technology or mental health – driving both a higher take-up of transfers and a higher probability of exiting. Finally, being in debt and having higher monthly housing expenditures reduce the probabilities of exiting both food and housing insecurity.

Figure 14. Determinants of exit rates: age, children, and income



Note: The reference group is the 0-19 age group for panel (a), childless households for panel (b), and households with 0 declared income for panel (c).

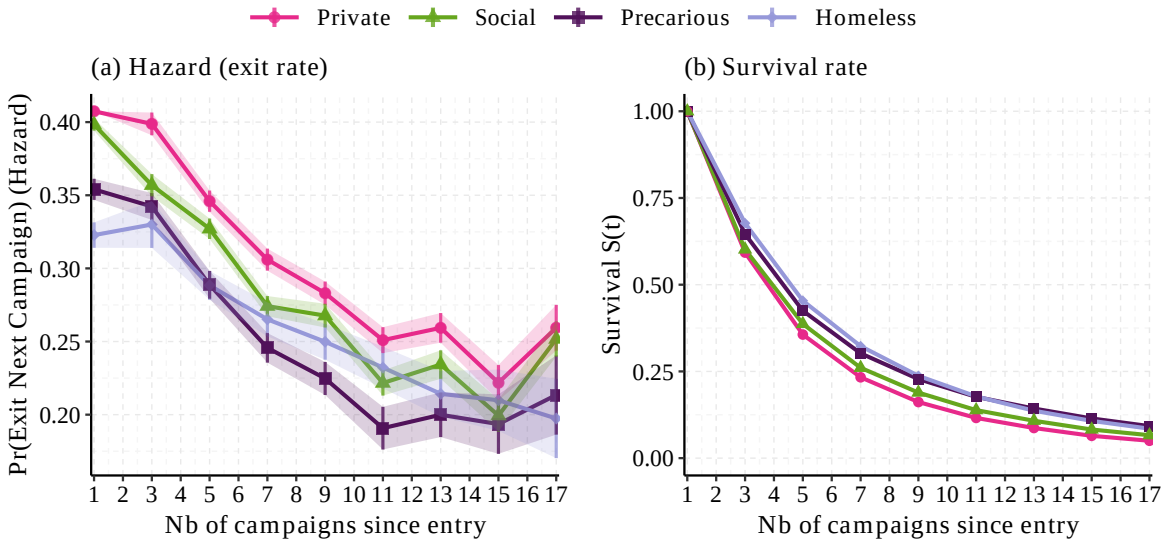
Third, our data exhibit a very strong duration dependence. We ask how likely an individual is to exit food insecurity, given that they have already been in our sample for 1 campaign (up to 4 months if they entered in the winter, and up to 8 months if they entered in the summer), two campaigns (1 full year), etc. Figure 15 shows the results for all categories of housing (at the time of their first entry into RDC).[69] We find that relative to the first entrants into the sample, and controlling for all other covariates, spending 3 years into the sample (6 campaigns) reduces the probability of exiting food insecurity by about 10 percentage points, regardless of initial housing status. Spending 5 years in extreme poverty reduces the probability of escaping this situation by 15 percentage points. These are similar orders of magnitude as comparing 20 vs. 60 year olds, or households receiving 0 vs. ∼600€ per month. The one-period-ahead exit rate converges to about 20-25% in the long run for all housing categories. Experiencing a repeat spell – i.e., returning to RDC after having already entered and exited in the past – has a small impact on the exit rates from the current spell.

[69]The estimates in Figure 15 are lower than the average exit rates reported in Table 1, because the former are one-period ahead exit rates (where one period lasts either 4 or 8 months) while the latter were one-year ahead exit rates (2 campaigns). Also recall that we define an exit from the sample as an absence from *two* successive campaigns.

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 housing insecurity as early as possible, and ensure that they are getting as much stability as possible with their newfound dwelling.

Notice finally that, in contrast to the descriptive statistics of Table 1, the housing-insecure are now the least likely to exit the sample – 5 to 10 pp below renters at any duration. Recall that the estimates in Figure 15 control for housing expenses. Thus, homeless households who spend significant amounts in shelter or hotel nights are less likely to escape food insecurity than a private tenant who spends the same in their rent – perhaps reflecting underlying unobserved characteristics. Figure 27 in the Appendix shows that the hazard rates recover their initial ranking if we remove these expenditure controls. Private and social housing tenants are then about 5 percentage points less likely to exit than housing-insecure households – presumably because they have a lower ability to adjust their non-discretionary spending (housing) on the intensive margin and must therefore rely on RDC for food support.[70]

Figure 15. Exit rates from food insecurity: duration dependence



Note: This reports the effect of duration×housing status in the individual exit model (2). The reference group is private housing with a spell duration of 1 campaign. Hazard rates are computed by adding the predicted average exit rate for newly arrived private renters (40.7%) to the duration-housing specific coefficients.

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

Taking Stock: Asymmetric Effects of Economic Shocks. We have shown that entry rates into food and housing insecurity are strongly and significantly impacted by the labor and housing markets of a living basin. By contrast, none of these location characteristics seem to have any meaningful impact on exits out of poverty (except for the industrial composition of the area). The key determinants of exit rates are, instead, household-level variables with, in particular, a very 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 food and housing insecurity 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 housing insecurity might, paradoxically, provide.

It is important to avoid mis-interpreting these results. We are *not* claiming that once a household enters deep poverty, they remain stuck in this situation and are unable to exit – recall that the exit rates are in fact fairly high, contradicting the hypothesis of a poverty trap. We are not saying either that location characteristics are irrelevant for the probability of exiting poverty – recall that our regressions include a location fixed effect, implying that permanent differences in local characteristics (e.g., whether an ALB is urban or rural) may give rise to systematic differences in the propensity of households to escape poverty. Rather, the correct way to understand the gap between the entry and exit rate elasticities with respect to location characteristics is analogous to the Shimer (2012) finding for unemployment fluctuations. This paper found evidence for the U.S. that the volatility of unemployment is overwhelmingly driven by the job finding rate (i.e., firms reduce hiring during recessions) rather than by the job destruction rate (i.e., firms do not significantly increase layoffs during recessions).[71] This does not mean that the job destruction rate is irrelevant – it is of course a critical driver of unemployment – but the point is that it exhibits relatively little cyclicality and is thus not driving its fluctuations. Similarly, in our case, exit rates from deep poverty hardly respond to variations in economic activity; fluctuations in food and housing insecurity are instead exclusively driven by the entry margin.

[71] The point of our argument is not to defend this finding; in particular it doesn't seem to hold as clearly in European economies; see, e.g., Petrongolo and Pissarides (2008). Our goal is to use a well-known finding in a different literature than ours as an analogy. Note furthermore that in our case, the entry margin *into* food and housing insecurity plays the role of the exit margin *out of* unemployment in Shimer (2012), and vice versa.

4.3 Counterfactual Analysis

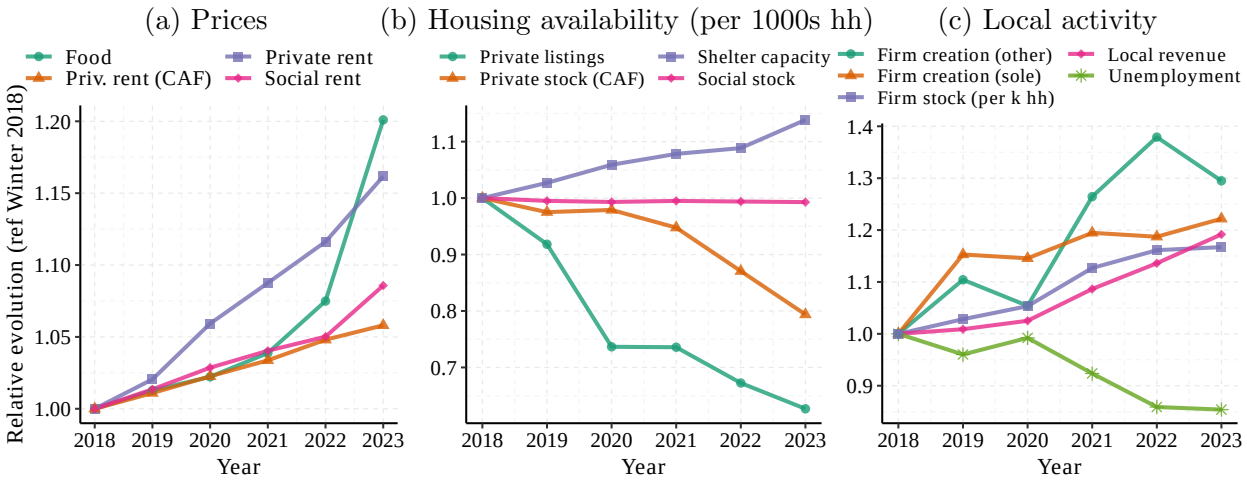
In this last subsection, we quantify the respective contributions of various economic shocks to the evolution of food insecurity and homelessness in France between 2018 and 2023 (the last year for which we observe all location-level macroeconomic variables, as of the writing of the current version of this paper). 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 2018 level – while letting all the others follow their actual course between 2018 and 2023.

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 16 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.[72] 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

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

Figure 16. Trend in economic variables



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.[73]

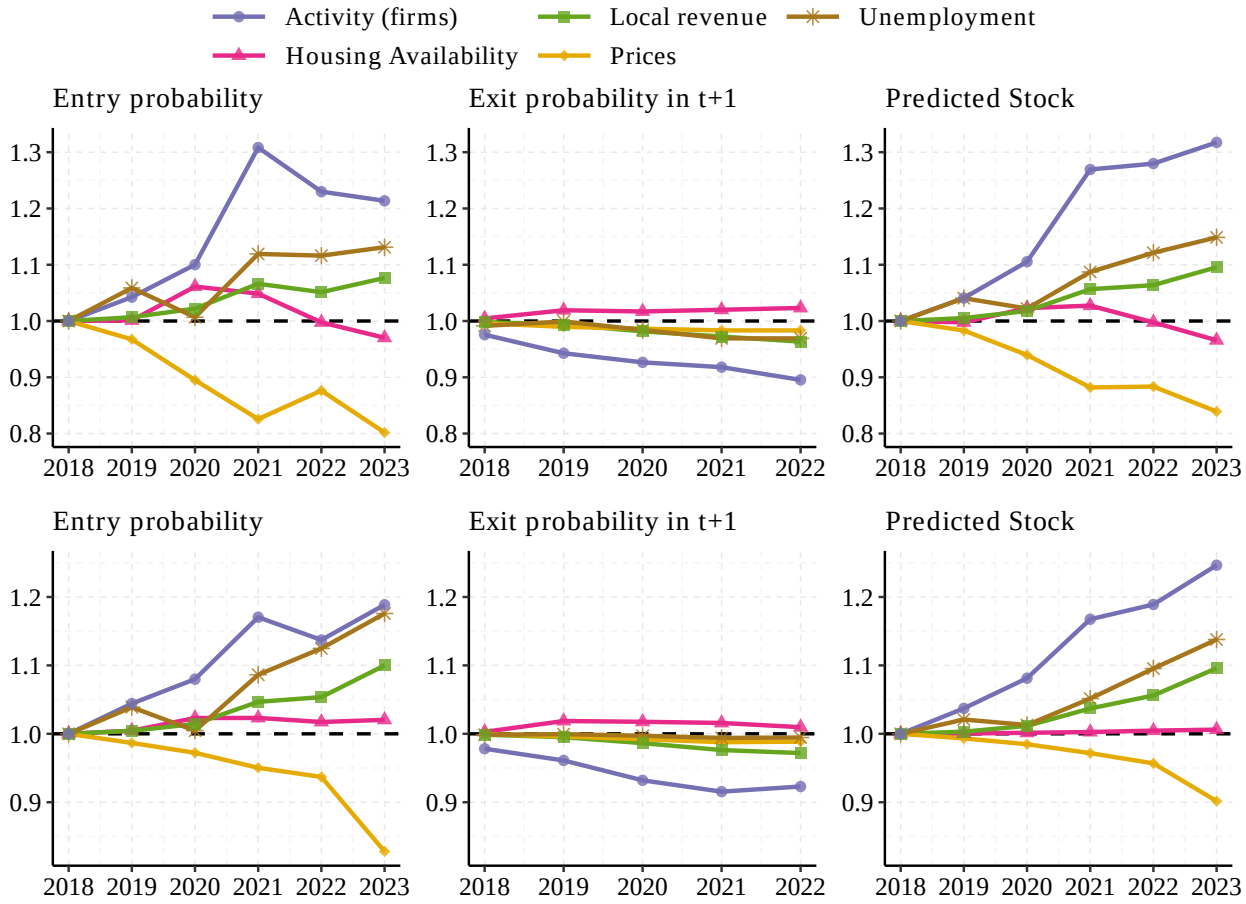
Note finally that active nationwide policies were implemented in 2020-21 in order to mitigate the negative consequences of the pandemic on poverty. Among others, these included extended employment protection (workers were able to reduce their labor supply while retaining their job and most of their earnings, 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.

Counterfactuals. Figure 17 reports the counterfactual evolutions of homelessness (top panel) and food insecurity (bottom panel). Each line in these graphs keeps one the following variables fixed: prices (food price index, both measures of private rents, social housing rents); housing availability (private rental listings, stock of social housing units, shelter availability);

[73] Source: here.

and economic activity (all firm-related variables, local revenue, unemployment rate). The dashed line in each panel represents the actual level of homelessness and food insecurity in each year, normalized to 1 throughout.

Figure 17. Counterfactual dynamics excluding key drivers: homelessness (top) and food insecurity (bottom)



Note: In order to easily reproduce the evolution of the stock of homeless or food-insecure households, these results come from additional models using only the winter campaigns where exit is simply defined as being absent from the sample in the following year.

Consider first the impact of one of the most striking macroeconomic developments of the past decade: high (food and rent) inflation. The yellow line in the figure shows that, if all prices had remained fixed at their 2018 level, the entry rate into homelessness would have been almost 20% lower by 2023 (with hardly any change in the exit rate), leading to an 18% lower number of homeless households relative to its true evolution. During the same period, homelessness rose by 61%. It would thus have increased by "only" 32% if prices had remained fixed.[74] We conclude that, all else equal, inflation is responsible for almost half

[74]If H denotes the number of resident homeless households in 2018, their actual number is $1.61H$ in 2023,

(48%) of the dramatic rise in homelessness during the period of our analysis. Consider next the variables related to economic activity. If the unemployment rate had remained at its 2018 level, the entry flows and the resulting number of homeless households and RDC recipients would have been about 15% higher than their actual level in 2023. Firm dynamism – the high rates of firm creation highlighted in Figure 16 – had an even larger impact. In other words, the significant decline in the French unemployment rate and the large amount of new firm creation after the pandemic significantly dampened inflows into homelessness and food insecurity. Notice finally that these counterfactual exercises clearly show that, apart from firm dynamism, none of the relevant macroeconomic variables have an important impact on the outflows from poverty – an insight we uncovered in the previous subsections: Offsetting the evolution of any of the location-level explanatory variables has an impact on exit rates from poverty that is an order of magnitude smaller than on entry rates.

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 demographics and dynamics of extreme poverty. Children and teenagers are vastly over-represented in both food and housing insecurity. And while these experiences are most often relatively short-lived, a very large share of the population is exposed to the risk of falling behind. Our second set of findings concerns the exposure of the poor to aggregate economic conditions. Local macroeconomic forces, including unemployment, private rents, social housing availability, and firm dynamism, are powerful drivers of entry into food and housing insecurity, while the same forces are largely irrelevant for exits. One of the most important 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. Prevention is therefore where policy should have the most leverage, through labor market stability, affordable housing supply, price stability, and early childhood interventions. For those who have already fallen behind, improvements in aggregate economic conditions are of little help; what matters most is early, targeted support, deployed before duration dependence makes an escape from deep poverty increasingly hard.

and would have thus been $0.82 \times 1.61H \approx 1.32H$ absent inflation.

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A Additional Results for Resident Households

A.1 Additional Figures and Tables

Acceptance Probability. Figure 18 shows the acceptance probability as a function of the distance to the eligibility threshold. Figure 19 shows the distribution of rest for living net of the eligibility threshold for both accepted and refused households.

RDC Usage Index. Figure 20 shows the distribution of the RDC "usage index" (frequency of visits) for winter and summer campaigns. The usage index measures the number of weeks a household visited RDC to pick up food, divided by the number of weeks between their first entry and the end of the current campaign. Thus, a lower index may reflect either infrequent visits at the RDC center throughout the campaign, or an early exit. Figure 21 shows how a household's within-campaign rank in the usage index relates to its exit rate in the next campaign.

Distance to Drop-In Centers. Figure 22 shows the cumulative distribution of the distance between recipients and their nearest drop-in center. Figure 23 replicates the same calculation for the Croix-Rouge (Red Cross) food distribution centers, and for urban vs. rural areas.

Age Distributions. Figure 24 shows the age distribution of resident households restricted to the 60+ year-olds (panel (a)), the 0-65 year-olds (panel (b)), the 0-18 year-olds (panel (c)), and to the household heads (panel (d)).

Finances. Figures 25 and 26 give the decomposition of average income and transfers along the life cycle into their respective components, for several subsamples (households with at least one member working; receiving RSA; in debt; and with disability).

Migration patterns. Table 5 shows the migration patterns for residents and non-resident households.

Comparison with Survey Data. Table 6 compares the RDC sample with survey data.

Figure 18. Left panel: Acceptance probability by year (summer campaign). Right panel: Acceptance probability by housing situation (before 2024, pooled years).

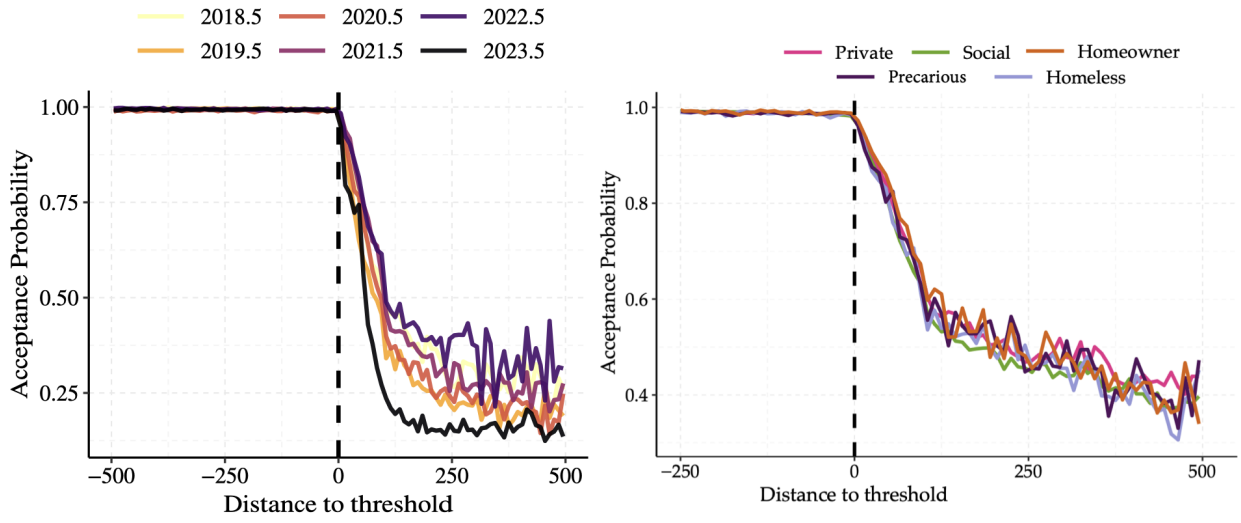


Figure 19. Distribution of rest for living, normalized by household-specific eligibility threshold.

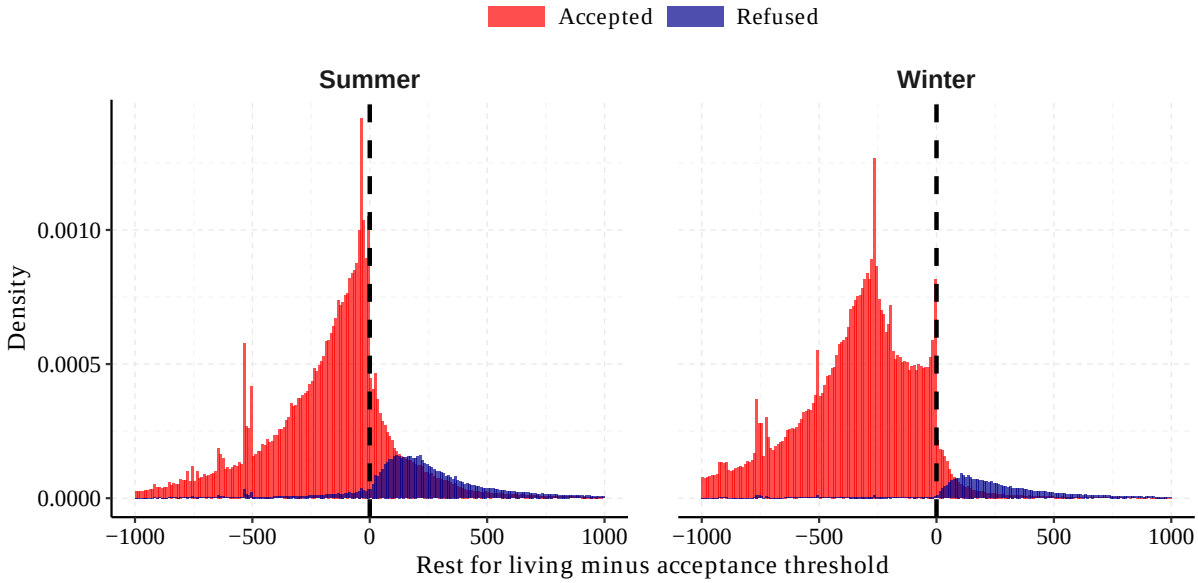
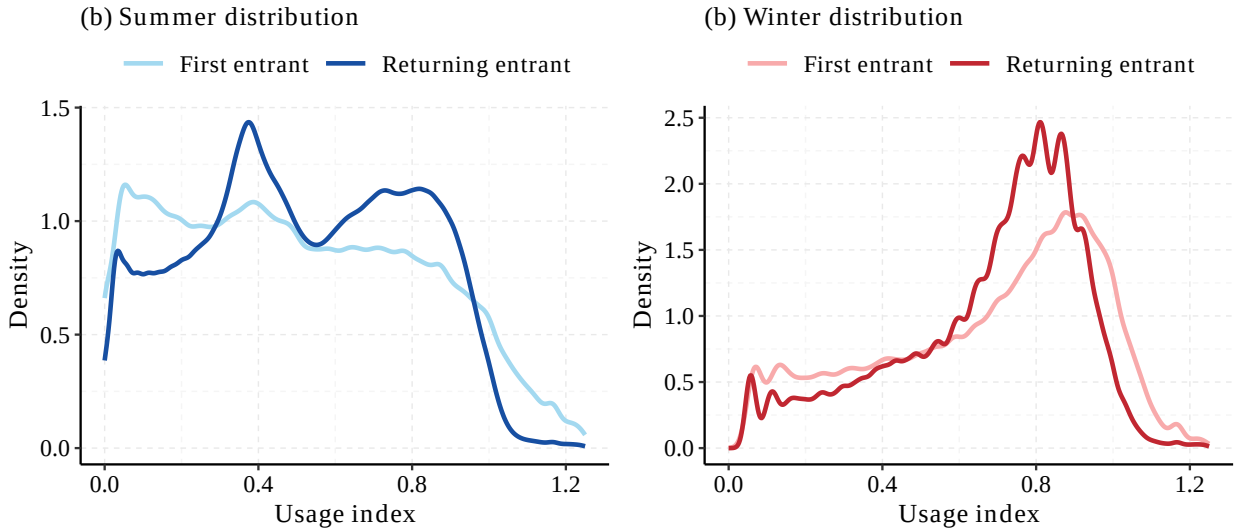


Figure 20. Reliance on RDC food assistance once a household is enrolled.



The usage index is calculed as the frequency at which recipients visit their RDC drop-in center to collect food within a given period. It is given by $\frac{\text{number of weeks the recipient collected food}}{\text{number of remaining weeks in the campaign since entry}}$. The usage index in summer is trimodal because some centers are closed during the summer while others are only partly open.

Figure 21. Probability of returning for the next campaign as a function of the percentile of the usage index.

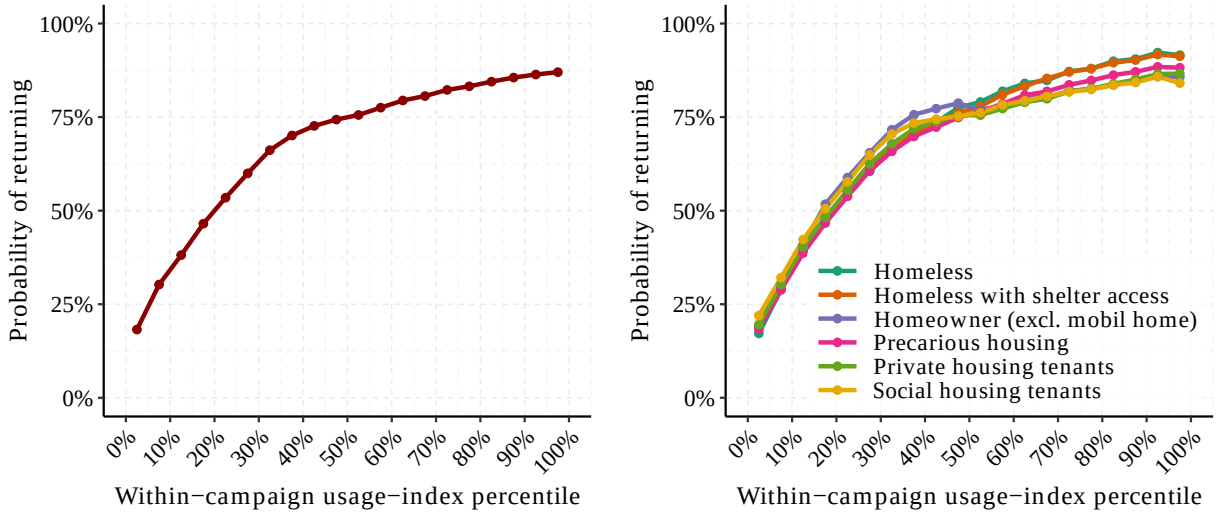
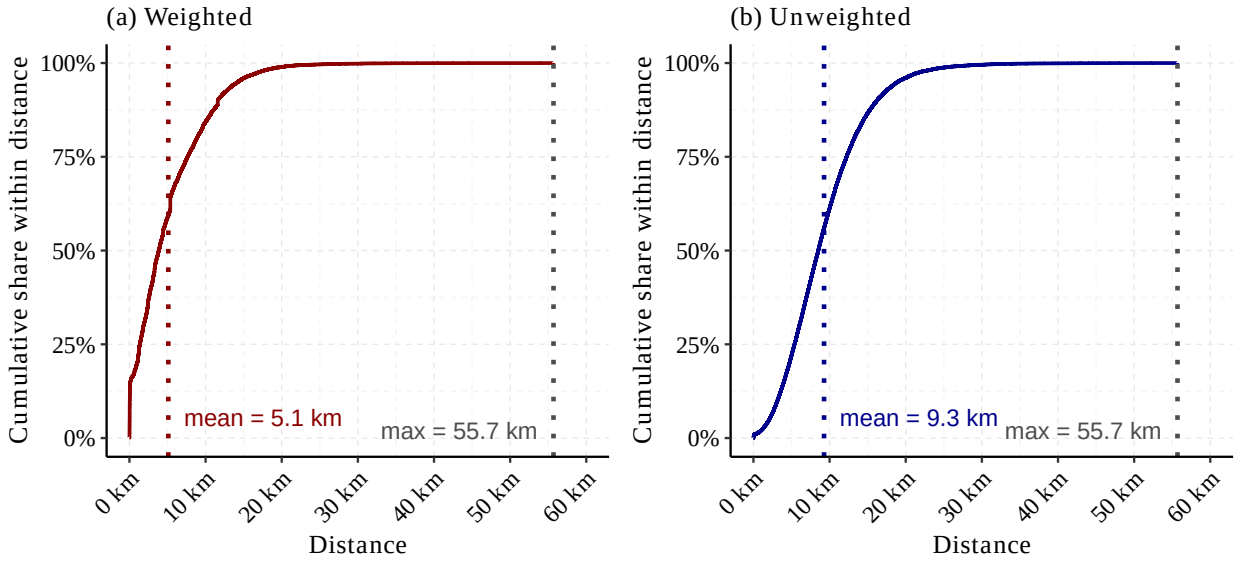


Figure 22. Distribution of distances to closest RDC drop-in center (left: population-weighted; right: unweighted).



Note: The distance from recipients to the nearest drop-in center is 5.1 km on average and at most 55.7 km, and 99% of recipients live within 20 km of a drop-in center. This is not an exact calculation. We observe the population of each *commune* in France (there are about 34,700 of them) and the zip code of each RDC center (there are about 6,300 zip codes). We assumed for simplicity that all of the inhabitants of a commune are located at its center point, and that each RDC drop-in center is located at the center point of its zip code. In practice, the distance is often close to zero for households located in the commune that contains the center of a zip code.

Figure 23. Distribution of distance to closest drop-in center: Comparison RDC vs Croix Rouge.

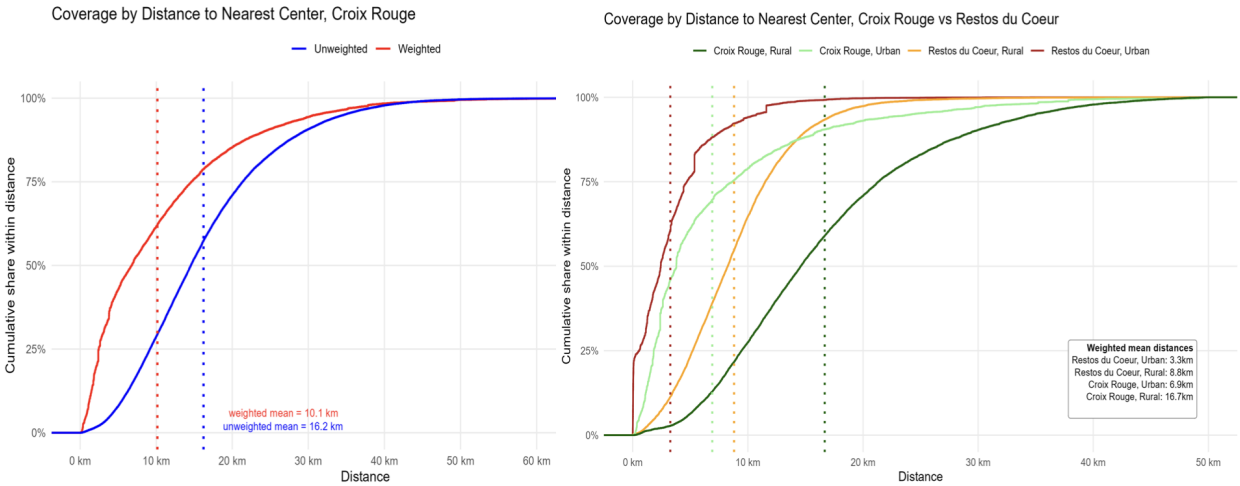
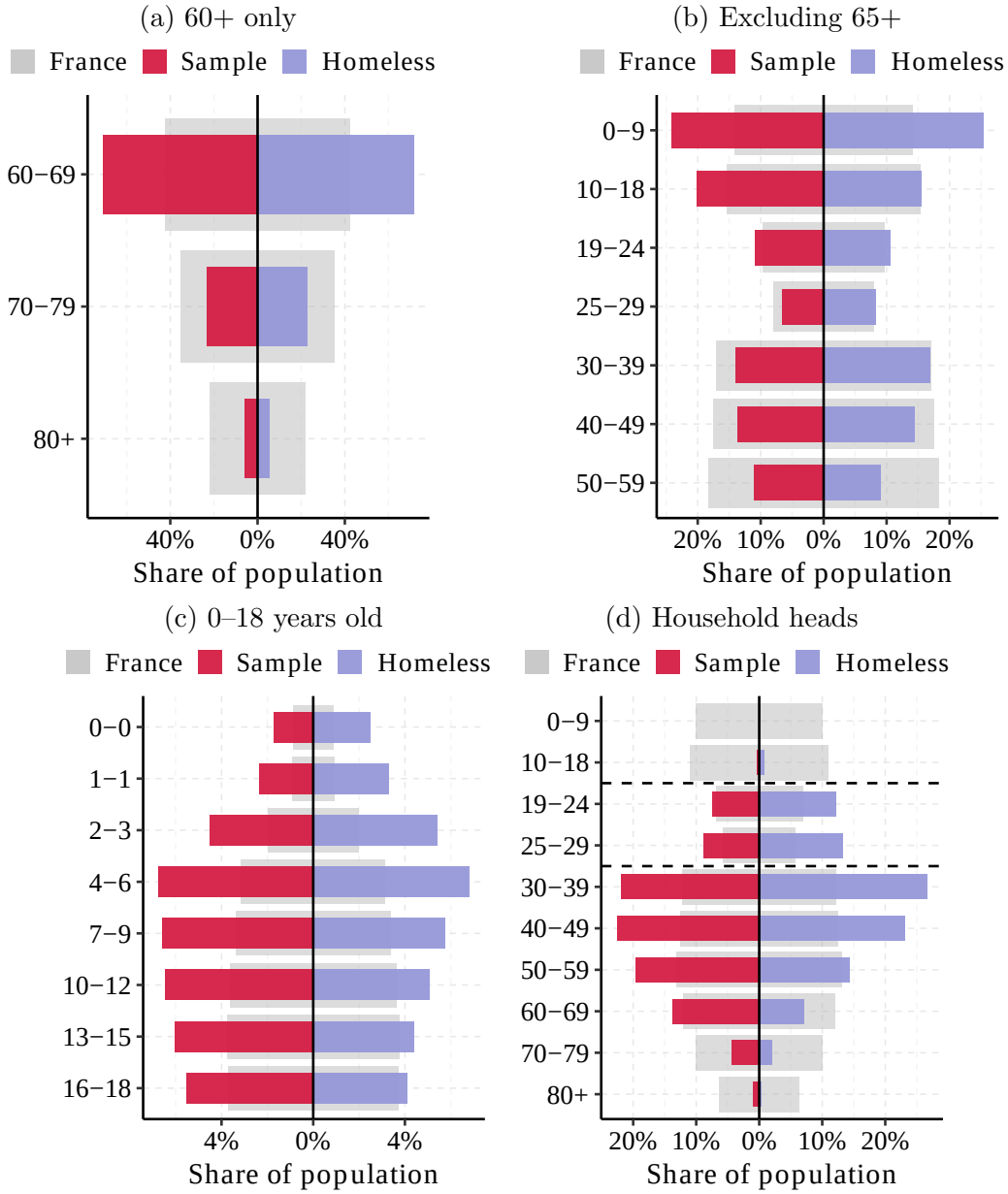


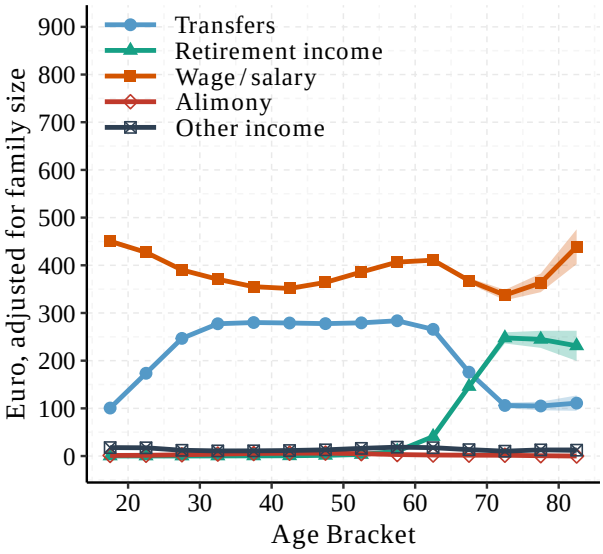
Figure 24. Age distribution (sample of residents)



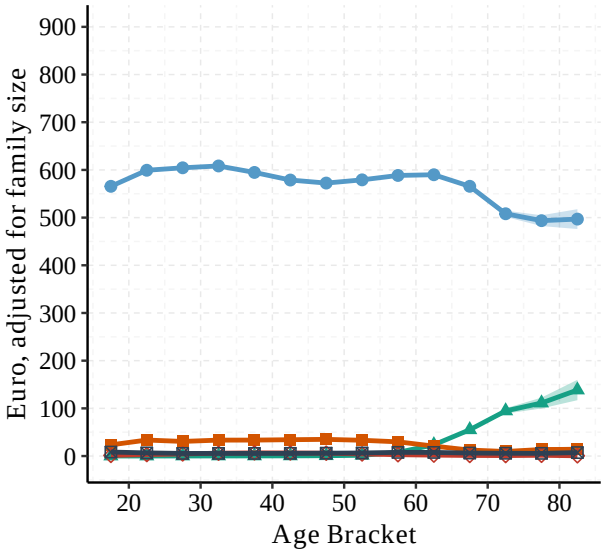
Note: The corresponding results for nonresident households are reported in Appendix B, Figure 30.

Figure 25. Decomposition of average income over the life cycle for selected sub-samples

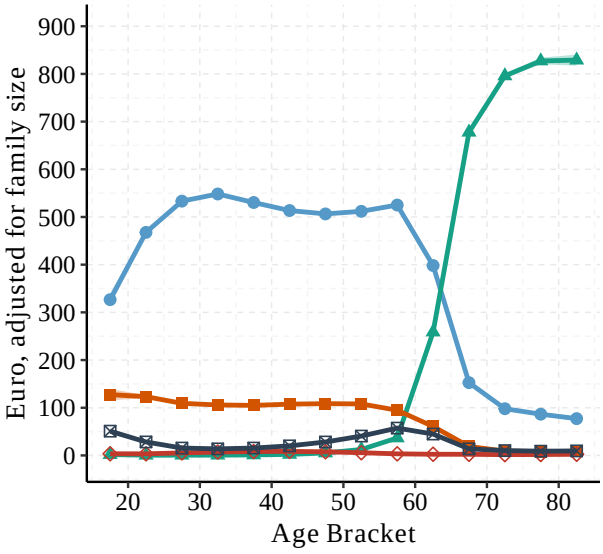
(a) Households who work



(b) Households with RSA



(c) Indebted households



(d) Households with disability

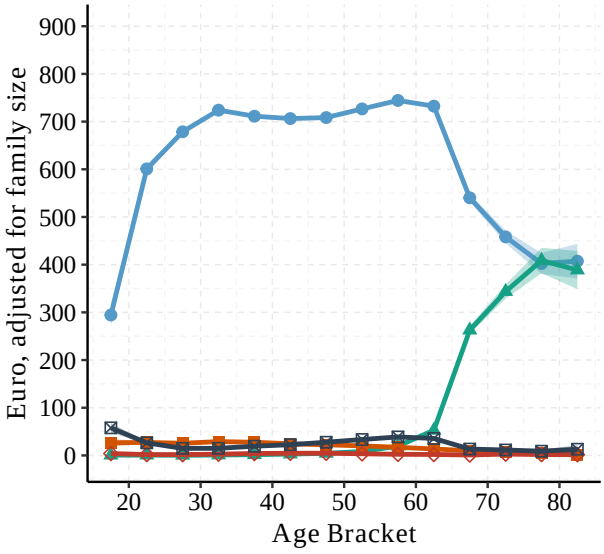


Figure 26. Decomposition of average transfers over the life cycle for selected sub-samples

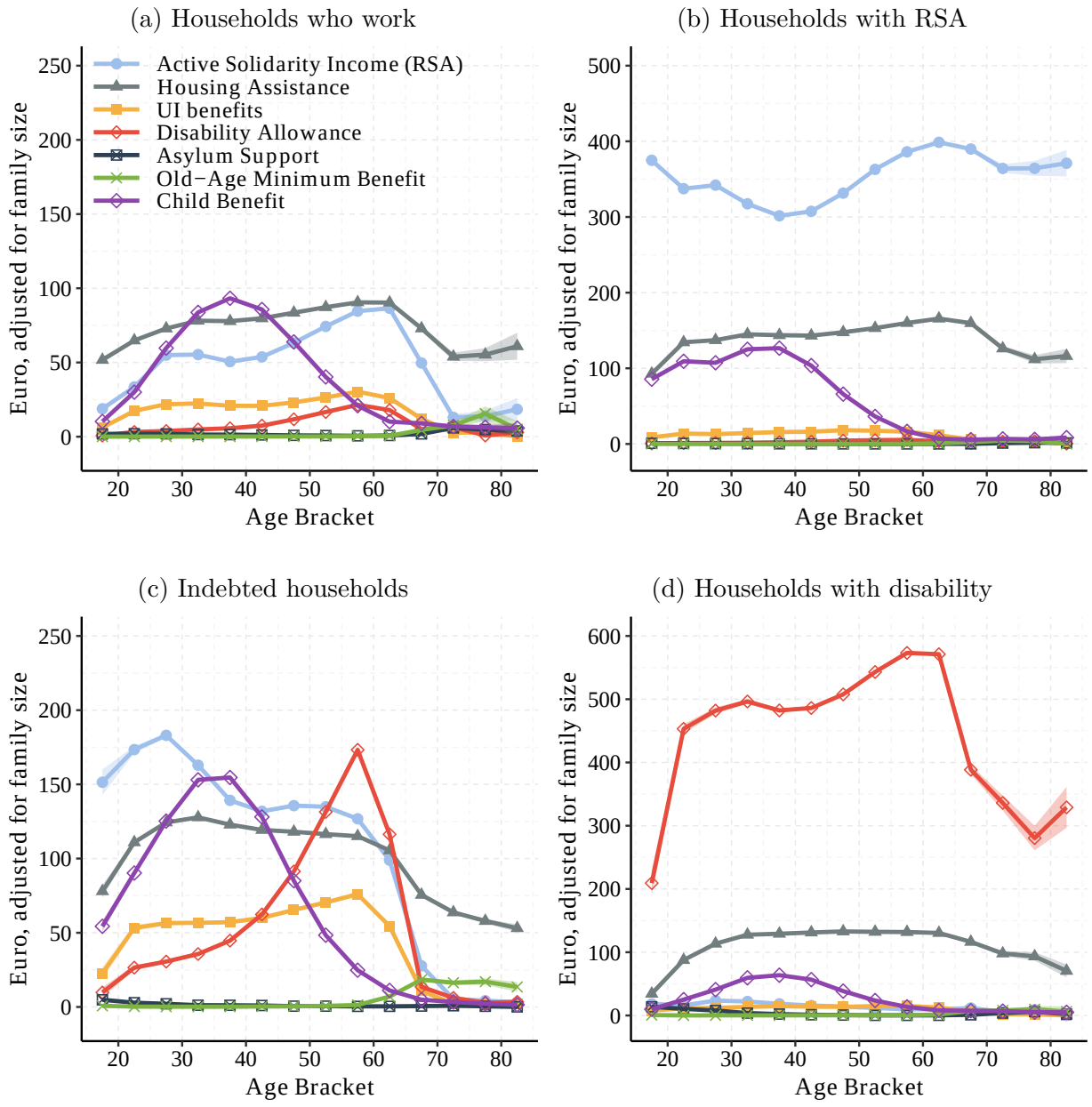


Table 5. Share of families who moved across geographical units, by housing and residency status

	Residents		Non-residents	
	Département	zip code	Département	zip code
Food insecurity	0.066	1.202	0.073	1.986
Housing insecurity	0.117	2.010	0.073	2.066

Table 6. 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

A.2 Alternative Specifications: Entry and Exit

A.2.1 Resident Sample: Location-Level Poisson and OLS Regressions

Table 7. Determinants of Entry Rates: Effects of Local Covariates (Poisson, ALB-level, Resident sample)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Log households	−1.665*	(0.996)	−0.240	(0.515)	0.335	(0.414)
N RDC centers (per k hh)	1.406	(0.958)	3.357***	(0.506)	3.684***	(0.421)
Log private rent	1.601***	(0.503)	0.237	(0.230)	−0.077	(0.125)
Log private listings (per k hh)	−0.084	(0.214)	0.006	(0.097)	0.056	(0.046)
Log private rent (CAF)	—	—	—	—	0.513**	(0.259)
Log private housing number (CAF)	−1.900***	(0.452)	−0.543**	(0.252)	0.045	(0.128)
Log social rent	−2.330***	(0.737)	−0.312	(0.368)	0.005	(0.181)
Log social housing stock (per k hh)	−0.839***	(0.324)	−0.220	(0.171)	0.087	(0.116)
Shelter capacity (per k hh)	−0.051***	(0.010)	−0.014**	(0.007)	0.002	(0.007)
Log unemployment	1.223***	(0.353)	0.922***	(0.222)	0.829***	(0.201)
Log food price index	−1.040	(0.819)	−0.573	(0.558)	−0.310	(0.393)
Log local revenue	0.490	(0.568)	−0.294	(0.332)	−0.485***	(0.183)
Log firm creation (sole propr.)	0.429***	(0.121)	0.129**	(0.066)	−0.014	(0.042)
Log firm creation (other)	0.118	(0.090)	0.045	(0.042)	0.007	(0.024)
Log firm closures (per k hh)	0.128	(0.128)	0.127**	(0.064)	0.028	(0.035)
Log firm stock (per k hh)	−0.194	(0.550)	−1.449***	(0.316)	−0.528**	(0.236)
Share manuf., mining & related	16.120***	(3.642)	1.897	(1.854)	−1.011	(1.045)
Share construction	−4.872*	(2.528)	0.968	(1.312)	0.900	(1.211)
Share wholesale, retail & food	1.490	(2.259)	0.564	(1.038)	−1.073*	(0.631)
Share public admin. & health	3.093	(2.464)	−0.272	(1.331)	1.218	(0.820)
Log avg. temp. × Winter	−1.369	(1.000)	0.510	(0.549)	0.955**	(0.390)
Log avg. temp. × Summer	−2.938	(2.330)	1.213	(1.531)	0.002	(0.974)
Log rain × Winter	0.008	(0.083)	−0.001	(0.046)	0.043	(0.038)
Log rain × Summer	−0.022	(0.068)	0.054	(0.049)	0.004	(0.044)
FE: area × period	Yes		Yes		Yes	
Observations	15,096		17,138		18,109	
Pseudo-R^2 (Squared Cor.)	0.872 (0.914)		0.884 (0.956)		0.941 (0.972)	

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

Table 8. Determinants of Exit Rates: Effects of Local Covariates (Weighted TWFE OLS, ALB-level, Resident sample)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Log RDC population	0.093***	(0.030)	0.175***	(0.022)	0.123***	(0.030)
N RDC centers (per k hh)	0.638	(1.215)	−0.590	(0.610)	−0.039	(0.391)
Log private rent	0.325	(0.335)	0.281	(0.195)	0.267**	(0.116)
Log private listings (per k hh)	0.063	(0.094)	0.077	(0.062)	0.093*	(0.049)
Log private rent (CAF)	—	—	—	—	0.039	(0.232)
Log private rent number (CAF)	0.074	(0.268)	0.111	(0.157)	−0.059	(0.109)
Log social rent	0.816*	(0.477)	0.745***	(0.245)	0.283*	(0.166)
Log social housing stock (per k hh)	−0.123	(0.358)	−0.144	(0.189)	−0.089	(0.106)
Shelter capacity (per k hh)	−0.008	(0.009)	−0.014**	(0.006)	−0.001	(0.004)
Log unemployment	−0.026	(0.300)	−0.148	(0.214)	0.103	(0.141)
Log CPI	−0.814	(0.782)	−0.883*	(0.519)	−0.646*	(0.366)
Log local revenue	−0.450	(0.552)	−0.055	(0.313)	0.052	(0.191)
Log firm creation (sole propr.)	0.126	(0.126)	−0.014	(0.073)	0.000	(0.048)
Log firm creation (other)	0.000	(0.081)	−0.025	(0.042)	−0.035	(0.026)
Log firm closures (per k hh)	−0.033	(0.061)	−0.003	(0.038)	−0.010	(0.027)
Log firm stock (per k hh)	−1.038*	(0.539)	−0.634*	(0.325)	0.000	(0.210)
Share manuf., mining & related	−0.689	(2.745)	1.794	(1.537)	−0.180	(0.923)
Share construction	−0.502	(2.714)	−0.117	(1.467)	1.554*	(0.914)
Share wholesale, retail & food	0.793	(1.570)	0.410	(0.930)	0.583	(0.645)
Share public admin. & health	3.465	(2.313)	0.143	(1.305)	1.734**	(0.846)
Log avg. temp. × Winter	−1.562**	(0.779)	−0.917	(0.604)	−0.990**	(0.413)
Log avg. temp. × Summer	1.397	(2.020)	0.817	(1.373)	2.079*	(1.145)
Log rain × Winter	−0.006	(0.056)	0.029	(0.037)	−0.022	(0.029)
Log rain × Summer	−0.035	(0.065)	0.018	(0.045)	0.036	(0.031)
FE: area × period	Yes		Yes		Yes	
Selection control (poly.)	Yes		Yes		Yes	
Observations	7,489		13,136		14,763	
Squared Cor.	0.399		0.365		0.391	

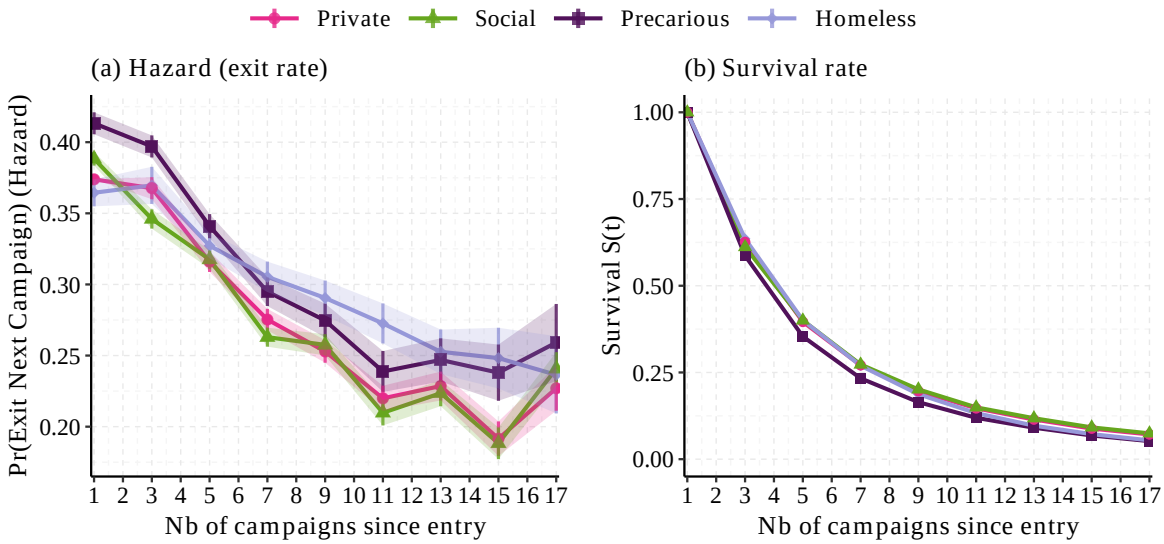
[a] Clustered (area_FE) standard errors in parentheses. Signif. codes: *: 0.10, **: 0.05, ***: 0.01.
[b] All covariates are lead variables one year ahead (at the time of exit).

Table 9. Determinants of Exit Rates: Effects of Local Covariates (Poisson, ALB-level, Resident sample)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Log RDC population	0.124***	(0.033)	0.170***	(0.021)	0.144***	(0.021)
N RDC centers (per k hh)	1.018	(0.952)	−0.348	(0.471)	−0.084	(0.386)
Log private rent	0.406	(0.330)	0.248	(0.176)	0.343***	(0.105)
Log private listings (per k hh)	0.036	(0.105)	0.006	(0.059)	0.035	(0.037)
Log private rent (CAF)	—	—	—	—	0.124	(0.190)
Log private rent number (CAF)	0.314	(0.256)	0.108	(0.147)	−0.073	(0.098)
Log social rent	−0.042	(0.462)	0.161	(0.257)	0.028	(0.122)
Log social housing stock (per k hh)	0.119	(0.313)	−0.031	(0.160)	−0.023	(0.094)
Shelter capacity (per k hh)	−0.001	(0.008)	−0.005	(0.005)	0.000	(0.004)
Log unemployment	−0.287	(0.291)	−0.317*	(0.182)	−0.018	(0.121)
Log CPI	−0.510	(0.767)	−0.404	(0.481)	−0.361	(0.315)
Log local revenue	0.316	(0.600)	0.113	(0.303)	−0.105	(0.173)
Log firm creation (sole propr.)	0.065	(0.110)	0.031	(0.064)	0.042	(0.039)
Log firm creation (other)	−0.099	(0.069)	−0.037	(0.034)	−0.015	(0.022)
Log firm closures (per k hh)	−0.062	(0.059)	−0.003	(0.034)	−0.024	(0.025)
Log firm stock (per k hh)	−0.415	(0.504)	−0.302	(0.294)	−0.053	(0.200)
Share manuf., mining & related	1.966	(2.474)	2.078	(1.343)	0.569	(0.836)
Share construction	0.852	(2.224)	−0.726	(1.170)	1.083	(0.740)
Share wholesale, retail & food	0.927	(1.344)	0.341	(0.820)	0.578	(0.564)
Share public admin. & health	3.573*	(1.989)	0.785	(1.050)	1.314*	(0.706)
Log avg. temp. × Winter	−0.893	(0.714)	−0.748	(0.524)	−0.371	(0.294)
Log avg. temp. × Summer	3.101*	(1.828)	1.720	(1.136)	2.442***	(0.806)
Log rain × Winter	0.004	(0.049)	0.024	(0.035)	−0.019	(0.025)
Log rain × Summer	−0.004	(0.055)	0.038	(0.036)	0.025	(0.026)
FE: area × period	Yes		Yes		Yes	
Selection control (poly.)	Yes		Yes		Yes	
Observations	7,196		12,991		14,753	
Pseudo-R^2 (Squared Cor.)	0.880 (0.971)		0.891 (0.981)		0.944 (0.986)	

[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 27. Exit rates from food insecurity: duration dependence, without controlling for housing expenditures.



Note: This figure reports the effect of duration × housing status in the individual exit model (2). The reference group is private housing with a spell duration of 1 campaign. 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 predicted average exit rate for newly arrived private renters (around 37% here) to the duration-housing 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.

A.2.2 Intensive-Margin Exit Variable: Usage Index

Table 10. Determinants of RdC Usage: Household-level Regressions (TWFE OLS, ALB-level)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Local covariates						
Log private rent	−0.139*	(0.081)	−0.100*	(0.054)	−0.082	(0.076)
Log private listings (per k hh)	0.023	(0.020)	0.005	(0.015)	−0.001	(0.020)
Log private rent (CAF)	—	—	—	—	−0.081	(0.115)
Log private housing stock (per k hh, CAF)	0.001	(0.059)	−0.004	(0.039)	0.006	(0.053)
Log social rent	0.067	(0.092)	−0.050	(0.057)	0.049	(0.084)
Log social housing stock (per k hh)	0.006	(0.095)	−0.006	(0.054)	0.082	(0.094)
Shelter capacity (per k hh)	−0.002	(0.002)	−0.001	(0.002)	0.001	(0.003)
Log unemployment	0.047	(0.086)	0.043	(0.061)	0.091	(0.081)
Log food price index	−0.130	(0.178)	−0.039	(0.141)	−0.049	(0.185)
Log local revenue	0.362***	(0.130)	0.327***	(0.093)	0.345**	(0.150)
Log firm creation (sole propr.)	−0.030	(0.026)	−0.036**	(0.017)	−0.061**	(0.027)
Log firm creation (other)	0.009	(0.020)	0.010	(0.010)	0.005	(0.017)
Log firm closures (per k hh)	−0.008	(0.015)	−0.002	(0.012)	−0.017	(0.015)
Log firm stock (per k hh)	0.183	(0.137)	0.037	(0.080)	0.114	(0.125)
Share manuf., mining & related	0.214	(0.666)	−0.116	(0.380)	−0.804	(0.593)
Share construction	0.325	(0.605)	−0.439	(0.377)	−0.595	(0.623)
Share wholesale, retail & food	−0.313	(0.375)	−0.108	(0.260)	−0.471	(0.393)
Share public admin. & health	−0.428	(0.596)	0.049	(0.332)	−0.492	(0.544)
Individual covariates						
Age						
Age bracket: 20–24	−0.002	(0.005)	0.002	(0.003)	−0.006**	(0.003)
Age bracket: 25–29	0.014***	(0.005)	0.020***	(0.003)	0.001	(0.003)
Age bracket: 30–34	0.036***	(0.005)	0.034***	(0.003)	0.019***	(0.003)
Age bracket: 35–39	0.048***	(0.005)	0.041***	(0.004)	0.035***	(0.003)
Age bracket: 40–44	0.059***	(0.005)	0.053***	(0.004)	0.046***	(0.003)
Age bracket: 45–49	0.076***	(0.005)	0.066***	(0.004)	0.060***	(0.003)
Age bracket: 50–54	0.096***	(0.006)	0.081***	(0.004)	0.073***	(0.004)
Age bracket: 55–59	0.123***	(0.006)	0.102***	(0.004)	0.088***	(0.004)
Age bracket: 60–64	0.138***	(0.006)	0.116***	(0.004)	0.102***	(0.004)
Age bracket: 65–69	0.148***	(0.007)	0.125***	(0.005)	0.127***	(0.005)
Age bracket: 70–74	0.151***	(0.009)	0.135***	(0.006)	0.149***	(0.006)
Age bracket: 75+	0.165***	(0.009)	0.138***	(0.006)	0.133***	(0.007)

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Table 10 – continued

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Income						
Income (CU): €1–400	0.002	(0.003)	0.001	(0.002)	0.018***	(0.002)
Income (CU): €400–500	−0.037***	(0.003)	−0.009***	(0.002)	−0.004	(0.003)
Income (CU): €500–600	−0.028***	(0.003)	−0.010***	(0.002)	−0.020***	(0.005)
Income (CU): €600–700	−0.025***	(0.004)	−0.008***	(0.003)	−0.028***	(0.006)
Income (CU): €700–800	−0.014***	(0.004)	−0.001	(0.003)	−0.042***	(0.013)
Income (CU): €800–900	−0.012***	(0.004)	0.000	(0.003)	−0.054***	(0.013)
Income (CU): €900–1000	−0.011**	(0.005)	0.008**	(0.004)	−0.099***	(0.013)
Income (CU): €1000+	0.000	(0.006)	0.019***	(0.005)	−0.033***	(0.011)
Number of children						
N children aged 0–3	0.041***	(0.002)	0.032***	(0.002)	0.049***	(0.002)
N children aged 4–8	0.026***	(0.001)	0.022***	(0.001)	0.024***	(0.001)
N children aged 9–12	0.029***	(0.002)	0.026***	(0.001)	0.023***	(0.001)
N children aged 13–16	0.027***	(0.002)	0.026***	(0.001)	0.024***	(0.001)
N children aged 16+	0.027***	(0.004)	0.021***	(0.003)	0.023***	(0.003)
Duration dependence: homelessness and housing instability						
Spell duration 0.5 year	−0.020***	(0.003)	−0.010***	(0.002)	—	—
Spell duration 1 year	−0.006**	(0.003)	0.016***	(0.002)	—	—
Spell duration 1.5 years	−0.007*	(0.004)	0.016***	(0.003)	—	—
Spell duration 2 years	0.002	(0.004)	0.034***	(0.003)	—	—
Spell duration 2.5 years	0.006	(0.005)	0.037***	(0.003)	—	—
Spell duration 3 years	0.014***	(0.005)	0.049***	(0.004)	—	—
Spell duration 3.5 years	0.014**	(0.007)	0.046***	(0.005)	—	—
Spell duration 4 years	0.015	(0.010)	0.058***	(0.006)	—	—
Duration dependence: food insecurity, private tenancy						
Duration 0.5 year	—	—	—	—	−0.056***	(0.011)
Duration 1 year	—	—	—	—	−0.043**	(0.017)
Duration 1.5 years	—	—	—	—	−0.022**	(0.011)
Duration 2 years	—	—	—	—	0.008	(0.012)
Duration 2.5 years	—	—	—	—	0.033**	(0.014)
Duration 3 years	—	—	—	—	0.045***	(0.017)
Duration 3.5 years	—	—	—	—	0.046**	(0.018)
Duration 4 years	—	—	—	—	0.032	(0.022)
Duration dependence: food insecurity, social tenancy						
Duration 0 year	—	—	—	—	−0.021***	(0.008)
Duration 0.5 year	—	—	—	—	−0.028***	(0.010)

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Table 10 – continued

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Duration 1 year	—	—	—	—	−0.009	(0.011)
Duration 1.5 years	—	—	—	—	0.003	(0.013)
Duration 2 years	—	—	—	—	0.027*	(0.015)
Duration 2.5 years	—	—	—	—	0.018	(0.019)
Duration 3 years	—	—	—	—	0.063***	(0.024)
Duration 3.5 years	—	—	—	—	0.066**	(0.027)
Duration 4 years	—	—	—	—	0.044	(0.045)
Duration dependence: food insecurity, homelessness						
Duration 0 year	—	—	—	—	0.009	(0.008)
Duration 0.5 year	—	—	—	—	−0.018**	(0.008)
Duration 1 year	—	—	—	—	−0.003	(0.008)
Duration 1.5 years	—	—	—	—	−0.004	(0.008)
Duration 2 years	—	—	—	—	0.007	(0.009)
Duration 2.5 years	—	—	—	—	0.026***	(0.009)
Duration 3 years	—	—	—	—	0.056***	(0.009)
Duration 3.5 years	—	—	—	—	0.060***	(0.010)
Duration 4 years	—	—	—	—	0.061***	(0.012)
Duration dependence: food insecurity, precarious housing						
Duration 0 year	—	—	—	—	0.013*	(0.008)
Duration 0.5 year	—	—	—	—	−0.012	(0.009)
Duration 1 year	—	—	—	—	0.022**	(0.009)
Duration 1.5 years	—	—	—	—	0.027***	(0.008)
Duration 2 years	—	—	—	—	0.055***	(0.009)
Duration 2.5 years	—	—	—	—	0.056***	(0.009)
Duration 3 years	—	—	—	—	0.082***	(0.011)
Duration 3.5 years	—	—	—	—	0.088***	(0.010)
Duration 4 years	—	—	—	—	0.083***	(0.013)
Other individual covariates						
Not first spell	−0.030***	(0.004)	−0.013***	(0.003)	−0.016***	(0.003)
Disabled	−0.005	(0.005)	0.004	(0.003)	—	—
In debt	−0.005	(0.004)	−0.008***	(0.002)	−0.016***	(0.006)
Rural (center)	0.046***	(0.009)	0.039***	(0.005)	0.008	(0.011)
HH type: Single man (ref: couple)	−0.089***	(0.003)	−0.069***	(0.002)	−0.072***	(0.002)
HH type: Single woman	−0.063***	(0.002)	−0.048***	(0.002)	−0.052***	(0.002)
Nationality: EU (ref: French)	0.026***	(0.005)	0.001	(0.005)	−0.032	(0.062)
Nationality: Other	0.071***	(0.003)	0.057***	(0.003)	0.025	(0.063)

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Table 10 – continued

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Education: N1 (ref: N0)	−0.004	(0.006)	−0.003	(0.004)	−0.001	(0.003)
Education: N4	−0.004	(0.006)	0.005	(0.005)	−0.005	(0.004)
Education: N7	−0.016**	(0.007)	−0.008	(0.006)	−0.009	(0.006)
Housing expenditure (CU): €1–100	0.003	(0.003)	−0.005**	(0.002)	0.036***	(0.006)
Housing expenditure (CU): €100–200	0.016***	(0.004)	0.008***	(0.002)	0.021***	(0.005)
Housing expenditure (CU): €200–300	0.020***	(0.004)	0.007***	(0.002)	0.028***	(0.005)
Housing expenditure (CU): €300–400	0.024***	(0.004)	0.006**	(0.003)	0.029***	(0.006)
Housing expenditure (CU): €400–500	0.028***	(0.005)	0.004	(0.004)	0.030***	(0.008)
Housing expenditure (CU): €500–600	0.023***	(0.007)	0.004	(0.005)	0.037***	(0.008)
Housing expenditure (CU): €600+	0.025***	(0.009)	0.003	(0.008)	0.028***	(0.009)
FE: area × campaign season	Yes		Yes		Yes	
FE: year-campaign	Yes		Yes		Yes	
Selection control (poly.)	Yes		Yes		Yes	
Observations	162,660		328,298		550,948	
Within R^2 (R^2)	0.120 (0.271)		0.081 (0.257)		0.072 (0.217)	

Standard errors clustered by area × campaign season in parentheses. Signif. codes: *: 0.10, **: 0.05, ***: 0.01.

Local covariates are lead variables one year ahead ($t+1$). The dependent variable is RdC usage in each household group. Dashes indicate coefficients not reported in the supplied results. Duration terms for food insecurity are interacted with housing status; the other two models use common spell-duration terms.

A.2.3 French Sub-Sample: Location-Level and Household-Level Regressions

Table 11. Determinants of Entry Rates: Effects of Local Covariates (Weighted TWFE OLS, ALB-Level, French sample)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Log households	−5.175***	(1.056)	−0.326	(0.698)	2.931***	(0.828)
N RDC centers (per k hh)	2.225**	(0.965)	4.011***	(0.541)	6.421***	(0.725)
Log private rent	4.324***	(0.457)	1.224***	(0.227)	0.399*	(0.225)
Log private listings (per k hh)	−0.018	(0.202)	0.056	(0.083)	0.126**	(0.056)
Log private rent (CAF)	—	—	—	—	0.084	(0.355)
Log private housing number (CAF)	−0.966**	(0.413)	−0.606***	(0.225)	−0.445**	(0.188)
Log social rent	−1.554***	(0.584)	−0.206	(0.300)	0.057	(0.272)
Log social housing stock (per k hh)	−1.071***	(0.289)	−0.341**	(0.173)	−0.012	(0.165)
Shelter capacity (per k hh)	−0.049***	(0.019)	−0.014	(0.012)	0.001	(0.015)
Log unemployment	0.837**	(0.416)	0.988***	(0.266)	1.590***	(0.402)
Log food price index	3.832***	(1.176)	0.882	(0.747)	0.411	(0.767)
Log local revenue	0.060	(0.607)	−0.243	(0.285)	−0.321	(0.235)
Log firm creation (sole propr.)	0.619***	(0.159)	0.077	(0.086)	−0.130	(0.097)
Log firm creation (other)	−0.045	(0.089)	0.026	(0.054)	0.039	(0.049)
Log firm closures (per k hh)	0.105	(0.136)	0.070	(0.062)	−0.003	(0.060)
Log firm stock (per k hh)	−2.991***	(0.609)	−1.276***	(0.377)	0.073	(0.402)
Share manuf., mining & related	15.010***	(3.281)	1.468	(1.979)	−1.426	(1.770)
Share construction	−2.598	(2.760)	0.657	(1.632)	0.863	(2.112)
Share wholesale, retail & food	6.777***	(2.199)	3.541***	(1.131)	0.531	(1.331)
Share public admin. & health	−1.585	(2.624)	−0.223	(1.603)	4.877***	(1.502)
Log avg. temp. × Winter	−4.041***	(1.245)	−0.875	(0.696)	0.263	(0.673)
Log avg. temp. × Summer	−1.899	(2.906)	0.671	(1.698)	−0.655	(1.243)
Log rain × Winter	0.042	(0.103)	0.008	(0.052)	−0.013	(0.071)
Log rain × Summer	0.019	(0.115)	−0.002	(0.065)	−0.010	(0.047)
FE: area × period	Yes		Yes		Yes	
Observations	17,765		17,653		18,108	
Squared Cor.	0.534		0.606		0.743	

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

Table 12. Determinants of Entry Rates: Effects of Local Covariates (Poisson, ALB-Level, French sample)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Log households	−6.485***	(1.297)	−1.194*	(0.634)	−0.446	(0.504)
N RDC centers (per k hh)	1.306	(1.105)	3.329***	(0.504)	3.614***	(0.462)
Log private rent	1.547***	(0.451)	0.492**	(0.192)	−0.005	(0.134)
Log private listings (per k hh)	−0.043	(0.186)	0.027	(0.086)	0.055	(0.043)
Log private rent (CAF)	—	—	—	—	−0.158	(0.257)
Log private housing number (CAF)	−1.643***	(0.367)	−0.516**	(0.210)	−0.070	(0.123)
Log social rent	−2.447***	(0.783)	−0.250	(0.348)	0.035	(0.181)
Log social housing stock (per k hh)	−0.881**	(0.369)	−0.372**	(0.174)	−0.086	(0.117)
Shelter capacity (per k hh)	−0.062***	(0.015)	−0.015*	(0.008)	−0.010	(0.008)
Log unemployment	0.814**	(0.381)	0.637***	(0.214)	0.656***	(0.195)
Log food price index	1.036	(0.953)	0.725	(0.592)	0.204	(0.398)
Log local revenue	0.298	(0.600)	−0.285	(0.252)	−0.334*	(0.176)
Log firm creation (sole propr.)	0.477***	(0.124)	0.095	(0.064)	0.044	(0.042)
Log firm creation (other)	0.071	(0.095)	−0.010	(0.043)	0.004	(0.025)
Log firm stock (per k hh)	−3.988***	(0.677)	−1.331***	(0.361)	−1.039***	(0.279)
Share manuf., mining & related	14.150***	(3.410)	1.958	(1.607)	0.394	(1.013)
Share construction	−3.840	(2.813)	2.378*	(1.347)	1.445	(1.268)
Share wholesale, retail & food	4.933**	(1.989)	2.621***	(0.961)	−0.324	(0.678)
Share public admin. & health	2.727	(2.793)	0.142	(1.403)	1.771**	(0.883)
Log avg. temp. × Winter	−1.204	(1.276)	−0.295	(0.611)	0.181	(0.409)
Log avg. temp. × Summer	−2.906	(3.130)	0.661	(1.909)	−0.506	(1.121)
Log rain × Winter	0.116	(0.088)	−0.004	(0.046)	0.025	(0.049)
Log rain × Summer	−0.026	(0.106)	0.019	(0.063)	0.024	(0.046)
FE: area × period	Yes		Yes		Yes	
Observations	13,974		16,529		18,007	
Pseudo-R^2 (Squared Cor.)	0.755 (0.880)		0.772 (0.933)		0.901 (0.961)	

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

Table 13. Determinants of Exit Rates: Household-level Regressions (French sample)

	Homelessness		Instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Local covariates						
Log private rent	0.142	(0.139)	0.019	(0.072)	0.064*	(0.035)
Log private listings (per k hh)	0.038	(0.051)	0.027	(0.024)	0.011	(0.012)
Log private rent (CAF)	—	—	—	—	0.056	(0.071)
Log private rent number (CAF)	0.007	(0.132)	−0.010	(0.064)	−0.049	(0.033)
Log social rent	−0.186	(0.246)	−0.130	(0.119)	−0.001	(0.052)
Log social housing stock (per k hh)	−0.078	(0.172)	−0.073	(0.077)	−0.029	(0.040)
Shelter capacity (per k hh)	−0.004	(0.004)	−0.004	(0.003)	−0.002	(0.002)
Log unemployment	0.000	(0.164)	−0.137*	(0.078)	0.041	(0.048)
Log CPI	0.158	(0.400)	0.088	(0.212)	0.043	(0.109)
Log local revenue	−0.151	(0.245)	−0.027	(0.131)	−0.017	(0.059)
Log firm creation (sole propr.)	0.084	(0.052)	0.024	(0.026)	0.009	(0.013)
Log firm creation (other)	−0.016	(0.039)	0.005	(0.017)	0.001	(0.008)
Log firm closures (per k hh)	−0.021	(0.030)	0.008	(0.016)	−0.006	(0.009)
Log firm stock (per k hh)	0.274	(0.277)	−0.105	(0.126)	0.004	(0.072)
Share manuf., mining & related	−2.953**	(1.466)	0.240	(0.620)	0.512*	(0.302)
Share construction	1.657	(1.239)	0.239	(0.575)	0.344	(0.288)
Share wholesale, retail & food	1.056	(0.823)	0.089	(0.375)	0.108	(0.214)
Share public admin. & health	1.657	(1.082)	0.974*	(0.501)	0.449*	(0.259)
Individual covariates						
Age + Income + # children	*see text and Figure 14.*					
Duration dependence	*see text and Figure 15.*					
Not first spell	−0.024**	(0.010)	−0.040***	(0.006)	−0.018***	(0.002)
Disabled	0.080***	(0.011)	0.029***	(0.006)	0.022***	(0.002)
In debt	−0.020**	(0.009)	−0.028***	(0.005)	−0.029***	(0.002)
Rural (center)	−0.028	(0.020)	−0.014*	(0.008)	−0.006	(0.004)
HH type: Single man (ref: couple)	−0.010	(0.007)	−0.037***	(0.004)	−0.038***	(0.002)
HH type: Single woman	0.021***	(0.007)	−0.013***	(0.004)	−0.029***	(0.002)
N children aged 0–3 (ref: none)	−0.030***	(0.007)	−0.012***	(0.004)	−0.011***	(0.002)
Education: N1 (ref: N0)	0.022	(0.027)	0.003	(0.013)	0.002	(0.006)
Education: N4	0.036	(0.025)	0.002	(0.014)	−0.004	(0.006)
Education: N7	−0.007	(0.033)	−0.014	(0.019)	−0.013	(0.009)
RdC consumption: 5–8 (ref: ≤ 5)	−0.118***	(0.007)	−0.113***	(0.004)	−0.113***	(0.002)
RdC consumption: 9–12	−0.193***	(0.007)	−0.185***	(0.004)	−0.176***	(0.003)
RdC consumption: 13–16	−0.279***	(0.007)	−0.285***	(0.004)	−0.277***	(0.003)
RdC consumption: 17+	−0.406***	(0.010)	−0.398***	(0.006)	−0.380***	(0.005)
FE: area × period	Yes		Yes		Yes	
Selection control (poly.)	Yes		Yes		Yes	
Observations	50,163		145,895		848,164	
Within R^2 (R^2)	0.087 (0.162)		0.089 (0.140)		0.093 (0.120)	

[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).

Table 14. Determinants of Exit Rates: Effects of Local Covariates (Weighted TWFE OLS, ALB-level, French sample)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Log RDC population	0.112***	(0.026)	0.162***	(0.018)	0.155***	(0.026)
N RDC centers (per k hh)	−0.678	(1.224)	−0.758	(0.564)	−0.218	(0.395)
Log private rent	0.403	(0.381)	0.259	(0.191)	0.238*	(0.121)
Log private listings (per k hh)	0.028	(0.122)	0.086	(0.067)	0.083	(0.052)
Log private rent (CAF)	—	—	—	—	0.073	(0.253)
Log private rent number (CAF)	−0.095	(0.307)	0.064	(0.169)	−0.051	(0.109)
Log social rent	0.697	(0.491)	0.526**	(0.252)	0.294*	(0.178)
Log social housing stock (per k hh)	−0.053	(0.376)	−0.171	(0.188)	−0.168	(0.116)
Shelter capacity (per k hh)	−0.017	(0.011)	−0.017**	(0.007)	−0.001	(0.005)
Log unemployment	0.113	(0.349)	−0.230	(0.200)	0.198	(0.138)
Log CPI	0.357	(0.904)	−0.171	(0.539)	−0.094	(0.392)
Log local revenue	−0.842*	(0.480)	−0.451	(0.287)	0.031	(0.198)
Log firm creation (sole propr.)	0.177	(0.133)	0.068	(0.073)	0.012	(0.047)
Log firm creation (other)	−0.033	(0.092)	−0.015	(0.043)	−0.064**	(0.028)
Log firm closures (per k hh)	0.020	(0.070)	0.039	(0.041)	0.012	(0.029)
Log firm stock (per k hh)	0.589	(0.648)	−0.356	(0.335)	0.148	(0.231)
Share manuf., mining & related	−3.507	(3.290)	1.487	(1.652)	−0.387	(0.969)
Share construction	3.541	(2.887)	0.128	(1.409)	1.499	(0.928)
Share wholesale, retail & food	2.153	(1.874)	0.489	(0.949)	0.380	(0.651)
Share public admin. & health	7.963***	(2.567)	1.589	(1.257)	1.504*	(0.867)
Log avg. temp. × Winter	−0.149	(0.920)	−0.249	(0.697)	−0.650	(0.399)
Log avg. temp. × Summer	−0.189	(2.464)	0.839	(1.571)	2.311*	(1.304)
Log rain × Winter	0.000	(0.064)	0.016	(0.044)	−0.003	(0.029)
Log rain × Summer	−0.087	(0.082)	0.009	(0.048)	0.032	(0.036)
FE: area × period	Yes		Yes		Yes	
Selection control (poly.)	Yes		Yes		Yes	
Observations	5,799		12,391		14,660	
Squared Cor.	0.414		0.371		0.382	

[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).

Table 15. Determinants of Exit Rates: Effects of Local Covariates (Poisson, ALB-Level, French sample)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Log RDC population	0.105***	(0.020)	0.174***	(0.014)	0.184***	(0.018)
N RDC centers (per k hh)	0.600	(0.991)	−0.356	(0.480)	−0.055	(0.390)
Log private rent	0.189	(0.347)	0.012	(0.180)	0.207**	(0.094)
Log private listings (per k hh)	0.063	(0.118)	0.028	(0.057)	0.048	(0.034)
Log private rent (CAF)	—	—	—	—	0.167	(0.190)
Log private rent number (CAF)	−0.010	(0.268)	−0.012	(0.137)	−0.048	(0.086)
Log social rent	0.118	(0.484)	0.177	(0.248)	0.027	(0.140)
Log social housing stock (per k hh)	−0.175	(0.317)	−0.199	(0.166)	−0.051	(0.098)
Shelter capacity (per k hh)	−0.007	(0.009)	−0.011*	(0.006)	−0.001	(0.004)
Log unemployment	−0.263	(0.317)	−0.242	(0.165)	0.095	(0.111)
Log CPI	0.708	(0.795)	−0.061	(0.456)	−0.053	(0.296)
Log local revenue	−0.622	(0.506)	−0.254	(0.276)	−0.247	(0.177)
Log firm creation (sole propr.)	0.165	(0.107)	0.073	(0.055)	0.037	(0.036)
Log firm creation (other)	−0.057	(0.084)	−0.001	(0.036)	−0.001	(0.022)
Log firm stock (per k hh)	−0.492	(0.648)	−0.731**	(0.340)	−0.097	(0.217)
Share manuf., mining & related	−6.249**	(2.809)	−0.094	(1.314)	0.411	(0.804)
Share construction	1.413	(2.388)	0.536	(1.187)	1.887***	(0.716)
Share wholesale, retail & food	1.719	(1.613)	1.095	(0.801)	0.777	(0.532)
Share public admin. & health	5.522***	(2.120)	1.957*	(1.031)	1.804***	(0.677)
Log avg. temp. × Winter	−0.097	(0.802)	−0.755	(0.550)	−0.285	(0.299)
Log avg. temp. × Summer	2.314	(1.694)	1.338	(1.052)	2.268***	(0.855)
Log rain × Winter	−0.040	(0.052)	0.007	(0.034)	−0.007	(0.024)
Log rain × Summer	−0.060	(0.051)	0.013	(0.032)	0.006	(0.024)
FE: area × period	Yes		Yes		Yes	
Selection control (poly.)	Yes		Yes		Yes	
Observations	5,560		12,180		14,646	
Pseudo-R^2 (Squared Cor.)	0.743 (0.961)		0.792 (0.974)		0.913 (0.984)	

[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).

A.3 Representativeness of the RDC Sample

Overall RDC Recipients: Comparison with Survey Data. Table 6 reports 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€.[75] 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.[76] 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 mis-measuring the bottom tail. (Note however that, as we argued in the main text, individuals in our sample should not be interpreted as necessarily the most *income*-poor but as the *consumption (ex-housing)*-poor, which we think is a far more relevant measure of poverty.)

The latter – mis-measurement of poverty in survey data – is the most likely explanation. Echoing the findings of Han et al. (2022) for the U.S., the bottom tail in surveys, just like the top tail, seems to be plagued by severe misrepresentation and misreporting. For instance, Table 6 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 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).[77] We find that the HFCS and EU-SILC cover a small fraction of the transfers relative to the total distributed amounts recorded in

[75] 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).

[76] 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.

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

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).

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.[78] As a result, extreme poverty and housing exclusion are systematically 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).[79] 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.[80] They confronted multiple reliable sources to estimate that France counted 333,000 homeless individuals in

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

[79] 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.

[80] Source: click here.

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 housing insecurity 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.[81,82] Including precarious and inadequate housing conditions, which we also observe in our data, further raises this population share to 0.62% or 124% of the OECD count, significantly more than estimated by the OECD (see Figure 1). Similarly, the French government gives an estimate of 350,000 homeless individuals (either sleeping rough or in shelters) in France;[83] if these numbers are estimated for 2025, again we observe 81% of the estimated total in our data. Although these outside estimates are naturally imprecise and can only give an order of magnitude at best, these comparisons suggest that our sample contains a very large share of the homeless population, as well as an additional 40% individuals in housing insecurity, who are also extremely difficult to capture in standard data sources.

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. First, as of 2024, RDC uses a different rest-for-living eligibility threshold for homeless households precisely to account for their lower housing expenses. Second, it appears that the homeless in our sample are mostly infra-marginal recipients, and hence likely to be systematically accepted into RDC. Figure 28 gives the breakdown of recipients by housing status in our sample. It shows that up until 2023, the share of housing-insecure (i.e., broadly homeless) recipients exhibits a strong seasonal

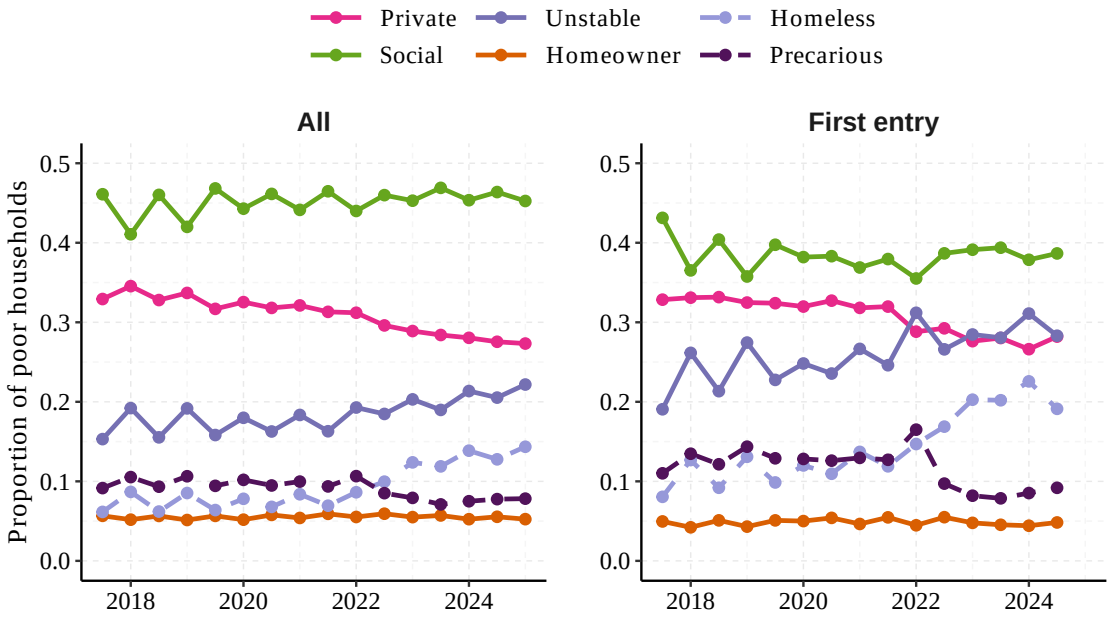
[81] More precisely, there are 210,005 (resp., 335,790) individuals who report being either homeless or in shelters (resp., in other housing insecurity situations) in the 2022 winter wave, and 228,647 (resp., 368,616) in the summer wave. Among the non-responses to the housing question, a fraction (around 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.

[82] 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.

[83] Source here.

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. Furthermore, Figure 11 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 31. 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, controlling for individual characteristics, the homeless are if anything slightly 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.

Figure 28. Housing Status Over Time.



Comparison with Outside Sources. Consider first the total number of homeless individuals in France. The DIHAL (*Délégation interministérielle à l'hébergement et à l'accès au logement*, French government) and INSEE give the following estimates: 93,000 in 2001, 143,000 in 2012, 333,000 in 2022, 350,000 in 2024 and 2025. The ETHOS statistics for 2022 are 5,500 in Category 1 (unsheltered or 'living rough'), 316,000 in Category 2 (emergency accommodation) and Category 3 (temporary accommodation, including 113,000 in refugee shelters), and 11,200 in Category 5 (unconventional dwellings). The 2025 ETHOS estimates are 334,000 in shelters and 590,000 staying with friends or family due to housing difficulties. As of year-end 2024, the French shelter system comprised 203,798 places 25% emergency shelters, 42% social hotels, and 32% longer-term transitional housing. Approximately 7,000 requests for emergency shelter go unmet on any given night. 3.3 million individuals have requested shelter since the inception of the management information system in 2014.

Consider next the duration of homelessness spells. In 2012, the INSEE found that the average duration of homelessness among French-speaking homeless people in 2011 was 9 months, including 1.7 months without shelter. A survey of 1,000 people living in general-purpose shelter accommodation in Paris in 2025 found that their average stay in that accommodation was 3.5 years (Observatoire du Samu Social de Paris). In their 2024-25 report, the Abbé Pierre foundation stated that among the 3,507 people found 'sleeping rough' in Paris (January 2025), 30% reported having been on the street for more than 5 years vs 12% for less than 3 months.

Consider finally the demographic characteristics of the homeless. In 2012, the INSEE found that across large cities and towns (defined as 20,000+ people), there were 81,000 homeless adults and 30,700 children using services; this means that ∼27.5% of the urban homeless population were children. They also found 38% wome, 62% single and childless. In 2021, the DIHAL found the following shares: 8.5% (resp., 2.7%) couples with (resp., without) children, 12% (resp., 13.9%) single women with (resp., without) children, 1.2% (resp., 39%) men with (resp., without) children, the remainder being groups with or without children. In 2021, the Secours Catholique found that 50% (resp., 42%, 35%) of their 15-25 (resp., 25-35, 35-45) year-old recipients were in housing insecurity in 2020. In 2023, the Secours Populaire found 36% couples with children and 26% de single-parent families among a subsample of their recipients. The UNICEF found that at least 2,159 children sleeping on the streets of France in 2025 (unsheltered); combining with DIHAL data (approximately 16,000 unsheltered in 2025), at least 13.5% of unsheltered population are children (this does not account for unsheltered individuals who do not call the 115 emergency housing hotline).

B Results for Non-Resident Households

B.1 Descriptive Statistics.

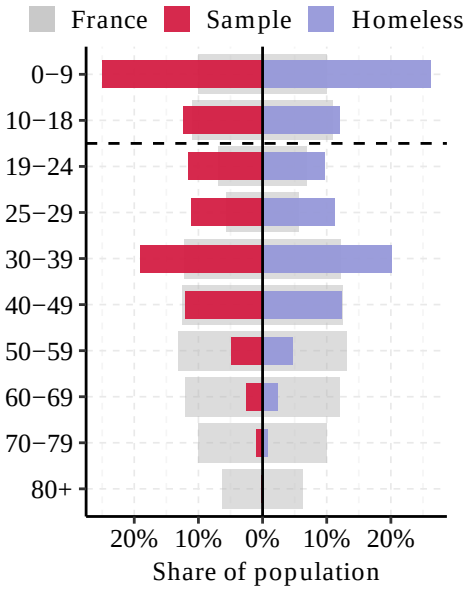
Average Statistics. Table 16 reports summary statistics for the nonresident sample. Its most striking feature is extreme economic precarity. Average total income per consumption unit is only €116.52, about 5% of the French benchmark of €2,256.98, and 85.7% of nonresident households live in housing insecurity. After housing expenses, only €83.99 per consumption unit remains, compared with €337 in the resident sample and €1,930.42 in France as a whole. Because this population is largely excluded from the transfer system, it faces deprivation far beyond what we observe for resident households.

Age Distribution. Figures 29 and 30 present the age distributions (with family structure of children) for the non-resident subsample.

Finances. Figure 31 shows the distribution of income, housing expenses, and rest for living for nonresident households. Figure 32 shows the evolution of average income and transfers over the life cycle.

Figure 29. Age distribution and family structure of children (sub-sample of non-residents).

(a) Age distribution (all)



(b) Children by family structure and age

		Sample		Homeless	
Age group		0−9	10−18	0−9	10−18
Couple	1 child	8.9%	5.3%	8.8%	5.2%
	2 children	18.8%	13.1%	18.0%	12.3%
	3+ children	28.0%	30.8%	26.2%	29.2%
Single mother	1 child	14.0%	8.2%	15.4%	9.0%
	2 children	13.4%	11.9%	14.3%	12.9%
	3+ children	15.3%	20.9%	15.7%	22.4%
Single father		1.3%	2.9%	1.1%	2.6%
No parent		0.3%	6.9%	0.3%	6.4%

Figure 30. Age distribution (sub-sample of nonresident)

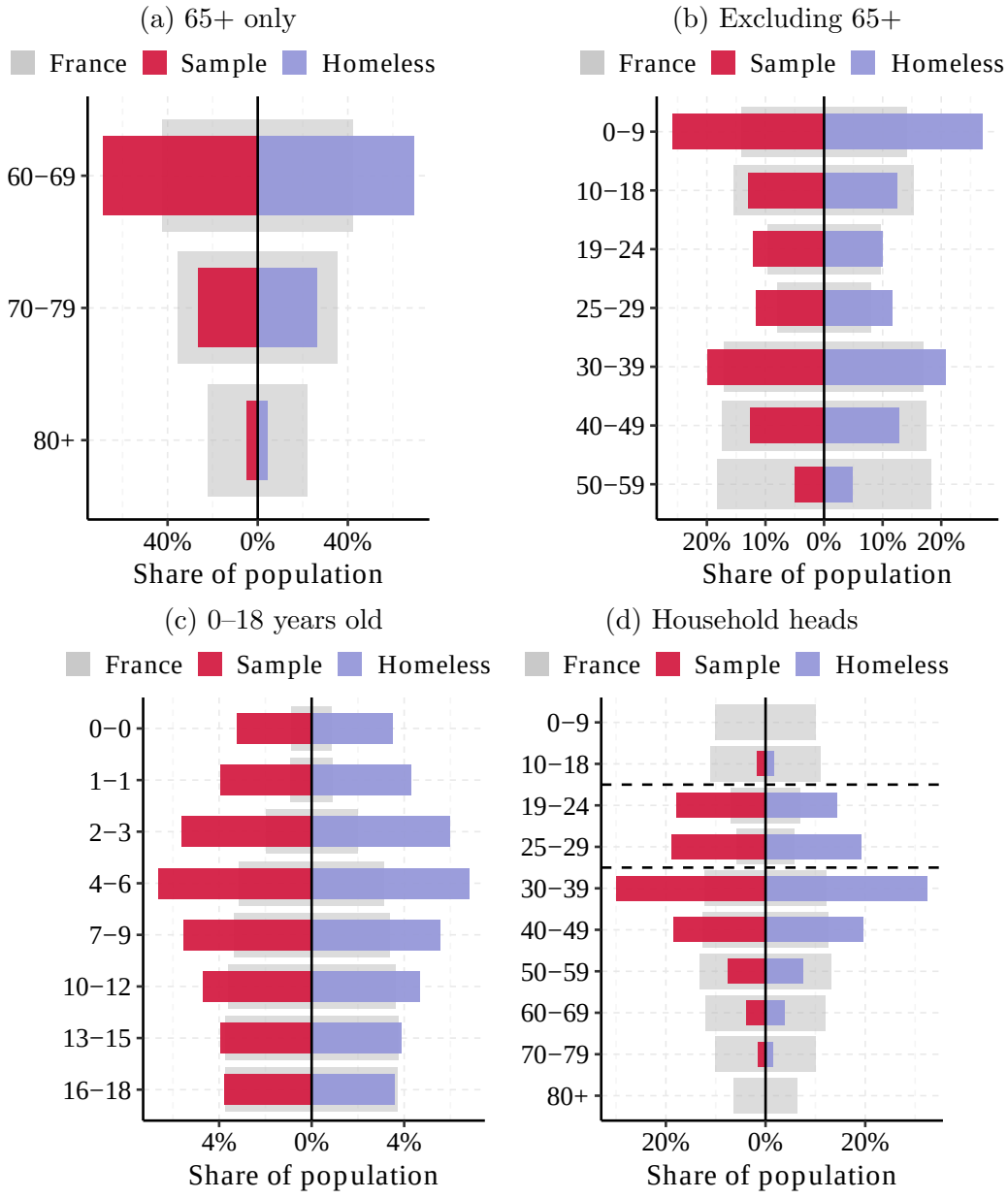


Figure 31. Subsample of Nonresident households. Left panel: Distributions of income per CU. Middle: Distribution of housing expenses per CU. Right panel: Distribution of non-housing consumption (rest for living) per CU.

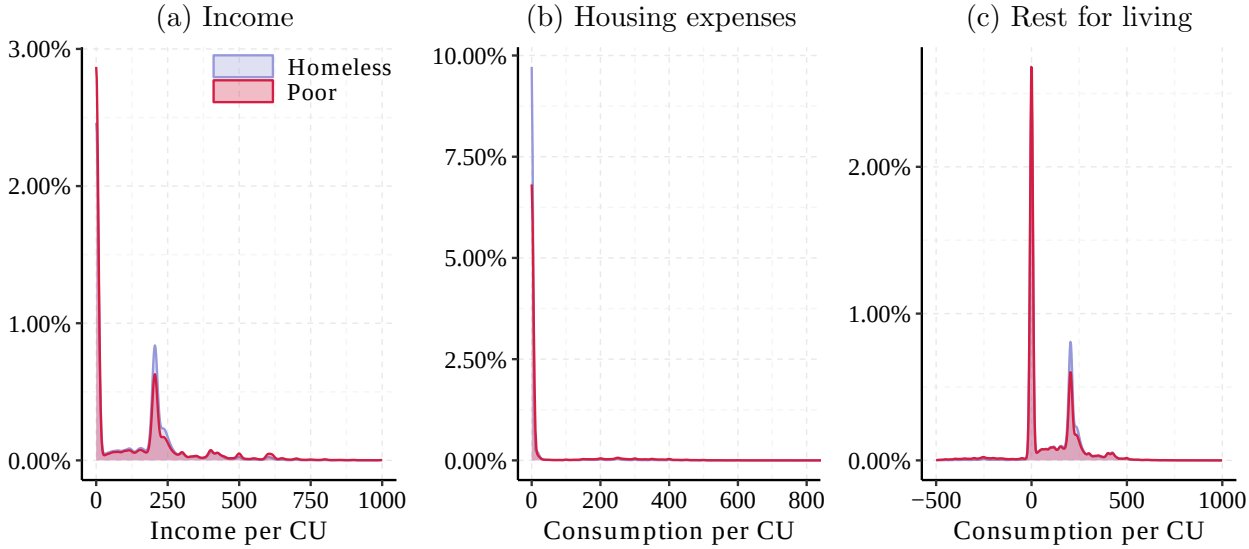


Figure 32. Decomposition of average income over the life cycle for non-resident households

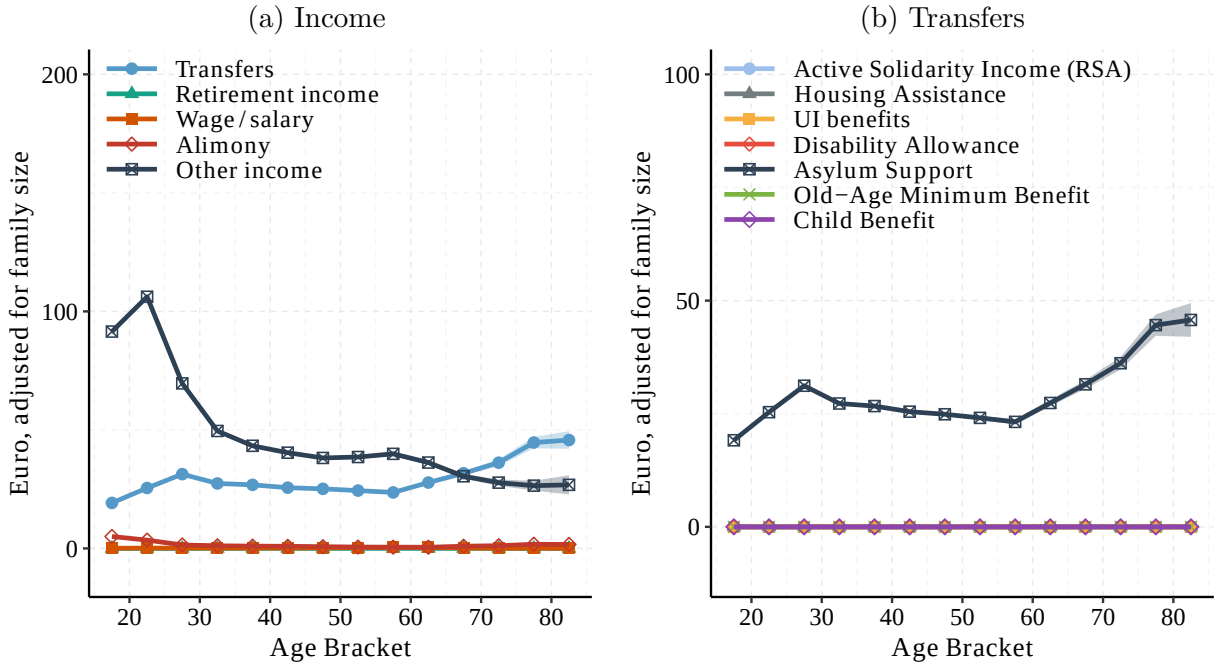


Table 16. Statistics for nonresidents: full sample and breakdown by housing status.

	RDC Nonresident Subsample								France[a]
	Full Sample		Private Rental		Social Housing		Housing instability		
Variable	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean
Demographics									
Age	35.18	(12.23)	32.45	(12.13)	34.07	(12.74)	35.56	(12.10)	54.7
Family consumption units	1.43	(0.581)	1.43	(0.620)	1.37	(0.587)	1.44	(0.576)	1.51
Couple	0.284	(0.451)	0.312	(0.463)	0.224	(0.417)	0.289	(0.453)	0.590
Single man	0.354	(0.478)	0.329	(0.470)	0.402	(0.490)	0.345	(0.475)	
Single woman	0.361	(0.480)	0.359	(0.480)	0.374	(0.484)	0.366	(0.482)	
# children	0.798	(1.17)	0.711	(1.17)	0.678	(1.19)	0.832	(1.17)	1.035
# children aged 0–3	0.240	(0.501)	0.147	(0.399)	0.163	(0.426)	0.262	(0.518)	
# children aged 4–12	0.423	(0.824)	0.425	(0.834)	0.379	(0.818)	0.436	(0.825)	
# children aged 13+	0.135	(0.428)	0.138	(0.429)	0.135	(0.442)	0.134	(0.424)	
Student	0.092	(0.289)	0.433	(0.496)	0.216	(0.411)	0.052	(0.223)	0.050
Retired / pre-retired	0.005	(0.069)	0.007	(0.081)	0.011	(0.105)	0.004	(0.064)	0.283
Finances (per CU)									
Work	0.013	(0.112)	0.021	(0.143)	0.027	(0.162)	0.008	(0.088)	0.530
Earnings	0.183	(8.73)	0.551	(16.83)	0.941	(18.22)	0.104	(6.55)	
Total income	116.52	(168.70)	255.18	(280.92)	200.28	(231.33)	103.16	(141.81)	2256.98
Transfers	30.83	(83.12)	11.73	(62.69)	59.47	(107.14)	33.64	(85.79)	188.74
Income w/o housing benefits	116.52	(168.70)	255.18	(280.92)	200.28	(231.33)	103.16	(141.81)	
Housing expenses	32.53	(102.20)	235.89	(185.43)	88.93	(150.68)	12.59	(62.03)	326.56
Expenses (incl. other regular)	39.03	(118.40)	274.26	(202.01)	116.53	(197.10)	14.58	(68.11)	
Total income minus housing expenses	83.99		19.29		111.35		90.57		1930.42
Resources left for consumption	77.48	(157.32)	-19.082	(262.52)	83.74	(230.90)	88.58	(135.20)	
Consumption according to RDC	45.51	(41.70)	39.43	(37.71)	41.61	(38.19)	47.67	(42.69)	
In debt	0.015	(0.122)	0.022	(0.146)	0.034	(0.180)	0.014	(0.118)	0.438
Debt repayment (for indebted)	29.54	(194.35)	85.17	(271.08)	94.58	(413.68)	8.43	(76.80)	
Survival in sample									
Goes to the charity next year	0.374	(0.484)	0.328	(0.469)	0.314	(0.464)	0.398	(0.489)	
Local covariates (ALB level)									
Annual income per capita (in k€)	17.05	(4.43)	16.20	(3.78)	16.54	(3.77)	17.29	(4.65)	17.13
Unemployment (broad) rate (%)	18.86	(3.49)	19.96	(3.87)	18.37	(3.55)	18.71	(3.45)	18.29
Private rent (€/sqm)	15.98	(6.24)	15.44	(5.48)	14.32	(5.57)	16.38	(6.45)	14.48
Private rent (CAF, €/sqm)	11.34	(3.50)	10.87	(3.17)	10.11	(3.24)	11.57	(3.59)	10.54
Social rent (€/sqm)	5.98	(0.834)	5.94	(0.774)	5.80	(0.846)	6.04	(0.847)	5.75
Private rentals per k hh	77.82	(33.48)	75.14	(31.76)	67.86	(31.07)	77.67	(33.27)	66.78
Social housing units per k hh	161.19	(58.13)	163.19	(66.59)	145.73	(63.26)	163.76	(56.33)	130.69
Shelter capacity per k hh	10.16	(5.80)	9.42	(5.63)	8.47	(6.09)	10.48	(5.78)	7.26
Price index	111.82	(9.16)	112.64	(9.48)	115.90	(9.07)	112.18	(9.27)	109.36
Firm stock (per k hh)	145.20	(50.11)	138.11	(43.42)	137.86	(43.74)	146.45	(51.98)	142.23
Urbanization									
City center	0.597	(0.490)	0.630	(0.483)	0.586	(0.493)	0.592	(0.492)	0.317
Suburb	0.338	(0.473)	0.302	(0.459)	0.286	(0.452)	0.353	(0.478)	0.379
Isolated city	0.048	(0.215)	0.046	(0.209)	0.103	(0.304)	0.043	(0.202)	0.090
Rural area	0.016	(0.125)	0.023	(0.151)	0.026	(0.159)	0.013	(0.111)	0.214
Share of observations	100%		7.41%		6.92%		85.67%		

[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 ALB averages or postal code averages (for urbanization), weighted by population, between 2018 and 2023.

B.2 Entry and Exit of Non-Residents

Table 17. Determinants of Entry Rates of non residents: Effects of Local Covariates (Weighted TWFE OLS, ALB-level)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Log households	−0.718	(1.075)	−1.069	(0.943)	−1.923**	(0.942)
N RDC centers (per k hh)	1.435**	(0.568)	1.218***	(0.429)	1.548***	(0.451)
Share of retired hh	−9.727***	(3.667)	−7.562**	(3.023)	−5.372*	(2.807)
Log private rent	0.720*	(0.426)	0.478	(0.333)	0.568*	(0.300)
Log private listings (per k hh)	0.214	(0.141)	0.112	(0.112)	0.098	(0.086)
Log private units (CAF) (per k hh)	0.056	(0.409)	0.373	(0.337)	0.299	(0.264)
Log social rent	−0.839*	(0.432)	−0.447	(0.335)	−0.409	(0.290)
Log social housing stock (per k hh)	−0.398*	(0.239)	0.075	(0.198)	0.079	(0.204)
Shelter capacity (per k hh)	−0.047***	(0.015)	−0.028**	(0.012)	−0.024**	(0.011)
Log unemployment	−0.571	(0.389)	−0.441	(0.339)	−0.250	(0.285)
Log CPI	−0.408	(0.948)	−0.054	(0.789)	0.812	(0.817)
Log local revenue	−1.516**	(0.600)	−1.451***	(0.499)	−0.830**	(0.384)
Log firm creation (sole propr.)	0.011	(0.114)	−0.062	(0.087)	−0.004	(0.080)
Log firm creation (other)	−0.021	(0.061)	−0.026	(0.048)	−0.010	(0.043)
Log firm cessation ($t+1$)	0.083	(0.105)	−0.038	(0.080)	0.022	(0.064)
Log firm stock (per k hh)	−2.418***	(0.600)	−2.747***	(0.520)	−2.081***	(0.470)
Share manuf., mining & related	−6.539***	(2.494)	−4.042**	(1.946)	−3.234*	(1.896)
Share construction	5.657**	(2.351)	5.617***	(1.814)	2.750*	(1.660)
Share trade, transport, accom. & food	−5.859***	(1.634)	−5.301***	(1.333)	−4.891***	(1.720)
Share public admin., educ., health & social work	−5.899***	(2.210)	−5.692***	(1.872)	−5.519***	(1.676)
Log avg. temp. × Winter	−0.906	(1.260)	1.043	(1.117)	0.777	(0.743)
Log avg. temp. × Summer	−0.378	(3.044)	4.231	(3.066)	4.021	(2.919)
Log rain × Winter	−0.112*	(0.064)	−0.006	(0.054)	0.007	(0.040)
Log rain × Summer	0.093	(0.123)	0.080	(0.095)	0.090	(0.103)
FE: area × campaign season	Yes		Yes		Yes	
FE: year-campaign	Yes		Yes		Yes	
Observations	17,768		17,652		17,668	
Squared Cor.	0.684		0.712		0.725	

Standard errors clustered by area × campaign season in parentheses. Significance codes: *: 0.10, **: 0.05, ***: 0.01.

Table 18. Determinants of Exit Rates: Non-resident Household-level Regressions (TWFE OLS, ALB-level)

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Local covariates						
Log households	-0.508	(0.385)	-0.587*	(0.339)	-0.579	(0.358)
N RDC centers	-0.369	(0.466)	-0.260	(0.408)	-0.175	(0.384)
Share of retired hh	-1.693	(1.234)	-1.463	(1.123)	-1.518	(1.157)
Log RdC population	0.039***	(0.010)	0.039***	(0.009)	0.048***	(0.011)
Log private rent	0.419***	(0.125)	0.378***	(0.108)	0.286***	(0.101)
Log private listings	-0.025	(0.039)	-0.034	(0.036)	-0.015	(0.040)
Log private housing stock (CAF)	-0.004	(0.097)	0.007	(0.091)	-0.082	(0.096)
Log social rent	-0.103	(0.221)	0.001	(0.199)	0.096	(0.177)
Log social housing stock	-0.102	(0.133)	-0.150	(0.115)	-0.185*	(0.105)
Shelter capacity	-0.007**	(0.003)	-0.007**	(0.003)	-0.006**	(0.003)
Log unemployment	-0.102	(0.116)	-0.048	(0.109)	-0.072	(0.113)
Log food price	-0.196	(0.318)	-0.125	(0.320)	-0.093	(0.339)
Log local revenue	0.089	(0.173)	0.103	(0.145)	0.008	(0.140)
Log firm creation (sole propr.)	0.038	(0.048)	0.021	(0.043)	0.042	(0.043)
Log firm creation (other)	-0.038	(0.028)	-0.041	(0.026)	-0.039	(0.026)
Log firm cessation (per k hh)	-0.021	(0.023)	-0.017	(0.021)	-0.004	(0.021)
Log firm stock (per k hh)	0.363*	(0.197)	0.316*	(0.183)	0.163	(0.181)
Share manuf., mining & related	1.679	(1.053)	0.645	(0.967)	-0.186	(0.988)
Share construction	-0.024	(0.894)	-0.559	(0.815)	-0.719	(0.822)
Share trade, transport, accom. & food	0.466	(0.533)	0.422	(0.529)	-0.159	(0.549)
Share public admin., educ. & health	2.027**	(0.812)	1.406*	(0.792)	0.841	(0.788)
Log avg. temp. × Winter	-0.117	(0.292)	0.050	(0.276)	-0.088	(0.282)
Log avg. temp. × Summer	0.669	(0.717)	0.606	(0.659)	0.999	(0.720)
Log rain × Winter	-0.037	(0.027)	-0.035	(0.022)	-0.030	(0.022)
Log rain × Summer	-0.013	(0.020)	-0.017	(0.018)	-0.016	(0.017)
Individual covariates						
Not first spell	-0.025***	(0.009)	-0.026***	(0.006)	-0.026***	(0.006)
In debt	0.056***	(0.014)	0.058***	(0.012)	0.055***	(0.011)
Student	0.005	(0.017)	-0.002	(0.012)	-0.015	(0.012)
Retired	0.083***	(0.024)	0.036**	(0.015)	0.080***	(0.016)
Suburb (ref: city center)	-0.020	(0.012)	-0.013	(0.010)	-0.014	(0.010)
Isolated city	-0.008	(0.032)	0.014	(0.026)	0.014	(0.023)
Rural	0.027	(0.021)	0.059***	(0.016)	0.066***	(0.015)

Continued on next page

Table 18 – continued

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
HH type: Single man (ref: couple)	0.099***	(0.004)	0.090***	(0.004)	0.088***	(0.003)
HH type: Single woman	0.029***	(0.003)	0.028***	(0.003)	0.031***	(0.002)
N children aged 0–3	-0.064***	(0.003)	-0.065***	(0.003)	-0.063***	(0.003)
N children aged 4–8	-0.015***	(0.002)	-0.016***	(0.002)	-0.013***	(0.002)
N children aged 9–12	-0.012***	(0.002)	-0.011***	(0.002)	-0.009***	(0.002)
N children aged 13–16	-0.005**	(0.003)	-0.004*	(0.002)	-0.002	(0.002)
N children aged 16+	-0.003	(0.006)	-0.001	(0.005)	0.004	(0.005)
Nationality: EU (ref: French)	0.029**	(0.012)	0.041***	(0.010)	0.036***	(0.009)
Nationality: Other	-0.042***	(0.008)	-0.047***	(0.007)	-0.057***	(0.008)
Nationality: Unknown	—	—	—	—	—	—
Housing: Homeless	—	—	-0.019***	(0.004)	—	—
Housing: Precarious	—	—	-0.010***	(0.003)	—	—
Age						
Age: 20–24	0.005	(0.007)	-0.001	(0.006)	0.009	(0.006)
Age: 25–29	0.008	(0.008)	0.001	(0.007)	0.011*	(0.006)
Age: 30–34	-0.013*	(0.008)	-0.020***	(0.007)	-0.009	(0.006)
Age: 35–39	-0.037***	(0.008)	-0.047***	(0.007)	-0.034***	(0.006)
Age: 40–44	-0.052***	(0.008)	-0.060***	(0.007)	-0.045***	(0.007)
Age: 45–49	-0.064***	(0.009)	-0.074***	(0.008)	-0.056***	(0.007)
Age: 50–54	-0.087***	(0.010)	-0.091***	(0.008)	-0.069***	(0.008)
Age: 55–59	-0.094***	(0.010)	-0.106***	(0.009)	-0.082***	(0.008)
Age: 60–64	-0.113***	(0.011)	-0.128***	(0.008)	-0.102***	(0.008)
Age: 65–69	-0.135***	(0.014)	-0.150***	(0.010)	-0.122***	(0.009)
Age: 70–74	-0.146***	(0.015)	-0.163***	(0.012)	-0.144***	(0.011)
Age: 75+	-0.115***	(0.017)	-0.151***	(0.013)	-0.124***	(0.012)
Income per consumption unit (EUR)						
Income: 1–400	-0.044***	(0.005)	-0.042***	(0.005)	-0.046***	(0.005)
Income: 400–500	0.006	(0.006)	0.013**	(0.006)	0.012**	(0.006)
Income: 500–600	0.089***	(0.014)	0.083***	(0.013)	0.076***	(0.009)
Income: 600–700	0.016	(0.028)	0.036	(0.025)	0.065***	(0.017)
Income: 700–800	0.067**	(0.027)	0.105***	(0.027)	0.151***	(0.020)
Income: 800–900	0.105***	(0.038)	0.119***	(0.034)	0.158***	(0.021)
Income: 900–1000	0.164***	(0.044)	0.202***	(0.040)	0.230***	(0.022)
Income: 1000+	0.205***	(0.030)	0.206***	(0.024)	0.238***	(0.019)
Education						

Continued on next page

Table 18 – continued

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Education: N1 (ref: N0)	0.003	(0.005)	-0.001	(0.005)	-0.001	(0.005)
Education: N2	0.006	(0.006)	0.003	(0.005)	0.003	(0.005)
Education: N3	0.001	(0.006)	0.002	(0.005)	0.002	(0.005)
Education: N4	-0.001	(0.007)	0.004	(0.007)	-0.001	(0.008)
Education: N5	0.002	(0.010)	0.000	(0.008)	0.007	(0.008)
Education: N6	0.008	(0.012)	0.008	(0.010)	0.000	(0.011)
Education: N7	0.031*	(0.017)	0.031**	(0.014)	0.029**	(0.013)
Education: N8	0.046**	(0.020)	0.035**	(0.015)	0.031**	(0.013)
Housing expenditure per consumption unit (EUR)						
Housing expenditure (CU): €1–100	-0.094***	(0.009)	-0.090***	(0.009)	-0.101***	(0.008)
Housing expenditure (CU): €100–200	-0.042**	(0.016)	-0.036***	(0.012)	-0.043***	(0.010)
Housing expenditure (CU): €200–300	-0.053**	(0.024)	-0.045**	(0.019)	-0.062***	(0.014)
Housing expenditure (CU): €300–400	-0.032*	(0.018)	-0.030**	(0.013)	-0.067***	(0.011)
Housing expenditure (CU): €400–500	-0.002	(0.042)	-0.026	(0.034)	-0.062***	(0.019)
Housing expenditure (CU): €500–600	-0.005	(0.074)	-0.021	(0.065)	-0.060*	(0.036)
Housing expenditure (CU): €600+	-0.041	(0.044)	-0.046	(0.038)	-0.064***	(0.023)
Duration dependence						
Spell duration: 0.5 year	0.079***	(0.006)	0.069***	(0.006)	—	—
Spell duration: 1 year	0.052***	(0.007)	0.026***	(0.006)	—	—
Spell duration: 1.5 years	0.038***	(0.009)	0.003	(0.007)	—	—
Spell duration: 2 years	0.023**	(0.010)	-0.022***	(0.008)	—	—
Spell duration: 2.5 years	-0.013	(0.011)	-0.055***	(0.008)	—	—
Spell duration: 3 years	-0.064***	(0.012)	-0.100***	(0.009)	—	—
Spell duration: 3.5 years	-0.093***	(0.014)	-0.134***	(0.011)	—	—
Spell duration: 4 years	-0.089***	(0.021)	-0.113***	(0.015)	—	—
Food insecurity: duration × housing status						
0.5 year × Private	—	—	—	—	0.121***	(0.018)
1 year × Private	—	—	—	—	0.080***	(0.020)
1.5 years × Private	—	—	—	—	-0.004	(0.019)
2 years × Private	—	—	—	—	-0.037**	(0.019)
2.5 years × Private	—	—	—	—	-0.079***	(0.022)
3 years × Private	—	—	—	—	-0.132***	(0.021)
3.5 years × Private	—	—	—	—	-0.153***	(0.028)
4 years × Private	—	—	—	—	-0.119***	(0.034)

Continued on next page

Table 18 – continued

	Homelessness		Housing instability		Food insecurity	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
0 years × Social	—	—	—	—	0.042***	(0.014)
0.5 year × Social	—	—	—	—	0.085***	(0.015)
1 year × Social	—	—	—	—	0.060***	(0.019)
1.5 years × Social	—	—	—	—	0.021	(0.022)
2 years × Social	—	—	—	—	0.014	(0.028)
2.5 years × Social	—	—	—	—	-0.035	(0.031)
3 years × Social	—	—	—	—	-0.087**	(0.039)
3.5 years × Social	—	—	—	—	-0.069	(0.055)
4 years × Social	—	—	—	—	-0.236***	(0.043)
0 years × Homeless	—	—	—	—	-0.049***	(0.012)
0.5 year × Homeless	—	—	—	—	0.032**	(0.013)
1 year × Homeless	—	—	—	—	-0.003	(0.014)
1.5 years × Homeless	—	—	—	—	-0.020	(0.013)
2 years × Homeless	—	—	—	—	-0.035**	(0.014)
2.5 years × Homeless	—	—	—	—	-0.069***	(0.015)
3 years × Homeless	—	—	—	—	-0.129***	(0.016)
3.5 years × Homeless	—	—	—	—	-0.154***	(0.017)
4 years × Homeless	—	—	—	—	-0.156***	(0.022)
0 years × Precarious	—	—	—	—	-0.010	(0.012)
0.5 year × Precarious	—	—	—	—	0.040***	(0.014)
1 year × Precarious	—	—	—	—	-0.043***	(0.014)
1.5 years × Precarious	—	—	—	—	-0.086***	(0.014)
2 years × Precarious	—	—	—	—	-0.136***	(0.014)
2.5 years × Precarious	—	—	—	—	-0.153***	(0.015)
3 years × Precarious	—	—	—	—	-0.170***	(0.015)
3.5 years × Precarious	—	—	—	—	-0.221***	(0.017)
4 years × Precarious	—	—	—	—	-0.139***	(0.022)
FE: area × campaign season	Yes		Yes		Yes	
FE: year-campaign	Yes		Yes		Yes	
Selection control (degree 3 poly.)	Yes		Yes		Yes	
Observations	388,837		540,959		585,718	
Within R^2 (R^2)	0.037 (0.106)		0.038 (0.106)		0.040 (0.104)	

Notes: Standard errors clustered by area × campaign season in parentheses. Significance codes: *: 0.10, **: 0.05, ***: 0.01.