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# The Impact of Minimum Income on Homelessness: Evidence from France\*

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## Abstract

In this paper, we use a Regression Discontinuity (RD) design to assess the impact of the French minimum income program (RSA) on users of accommodation and meal distribution services. In France, childless adults younger than 25 face hard-to-meet eligibility conditions to enroll in the minimum income program. The restrictive requirements generate a “jump” in the number of recipients at ages around 25. We find that the RSA benefit reduces the homelessness rate by 22% among young adults ages 22 to 27 in cities with more than 20,000 inhabitants in France. This result is mostly driven by new RSA recipients who have started paying partial rent to third parties, such as associations, NGOs, and/or acquaintances, and the probability of becoming a regular tenant increases after age 26. We find that receiving the RSA reduces demand for (almost) free meals at meal distribution services, and individuals report having more meals at home, especially dinners. The program’s effect on the number of entries in emergency shelters is statistically significant, but recidivism into homelessness declines around ages 26-27, when permanent housing seems to stabilize. We perform a sensitivity analysis to test how changes in the definition of homelessness may affect our results, and employ a trimming procedure to deal with potential attrition after age 25. The results confirm our core findings. Finally, we simulate the effects of lowering the program’s minimum age eligibility on the probability of being homeless. Despite the large additional costs compared with the current system, our findings suggest that if these programs were directed to the homeless, over 60% of expenditures would be compensated for savings in social assistance costs to the homeless.

***Keywords:*** Extreme Poverty, Homeless, Regression discontinuity, France, Welfare

***JEL:*** H2, I3, H4

# 1 Introduction

Over the past 40 years, homelessness has exploded as a social issue that demands the attention of public authorities in high-income countries such as France. The standard approach to mitigating homelessness has been to provide emergency shelters, rapid rehousing programs, and transitional housing services. More recently, financial assistance has been added as a prevention strategy. However, despite a large literature on homelessness and its determinants, there is still scant empirical evidence on the impact of cash assistance programs on homelessness (B. O’Flaherty, 2019).

In this paper, we investigate the impact of the French guaranteed minimum income program on users of meal distribution and accommodation services. The RSA (Revenu de Solidarité Active) is a cash transfer program with no time limit that targets a broad group of low-income households that are able to work. It covers about 2 million households and acts as a last resort for those who are not eligible for other benefits. In 2012, program participation could take 2 forms: the base RSA and RSA Activity. The base RSA is a guaranteed minimum income program for households with no earned income, and RSA Activity is supplementary income for households with activity income but whose resources fall below a threshold.

A key identification challenge here is self-selection, since the probability of treatment may correlate with individuals’ unobserved characteristics. To overcome this potential source of bias, we exploit an age eligibility threshold using a regression discontinuity design (RD) to evaluate the program’s impact on different outcomes, such as homeless status, number of meals taken at meal distribution centers, and entries in shelters. In France, childless adults younger than 25 face hard-to-meet eligibility conditions in order to enroll in the minimum income program: In addition to the income means test, they must have worked at least 2 years over the last 3 years (3,214 hours). This condition is especially restrictive, since this cohort faces the highest unemployment rate in France (25.3% in 2013) and was particularly hit by the economic crisis in the early 2010s. These eligibility requirements generate a “jump” in the number of recipients at age 25. By comparing the outcomes of individuals of similar age, but who barely meet or barely miss the age eligibility criterion, we can accredit differences to the RSA program (Imbens and Lemieux, 2008).

Homelessness is predominantly an urban issue. In the US, the vast majority of the 550,000

homeless are concentrated in large urban centers. Similarly, the most recent figures for France estimate that less than 10% of the nearly 150,000 homeless people live in rural areas (Yaouancq et al., 2013). Homelessness inflicts a substantial financial burden on governments. Estimates show that the average cost per homeless person per year is U\$13,661 in the US and €16,563 in France. In the US, federal funding for local organizations to combat homelessness more than doubled over the last decade, reaching U\$6.1 billion annually (USICH, 2018). In France, the COVID-19 pandemic has led to more than €450 million of additional credits for assistance that targets the homeless (CAE, 2020). The private costs of homelessness are also significant. Compared with the general population, the homeless display higher mortality rates, more exposure to violence, and a higher incidence of psychological disorders (Hodgson et al., 2013; Morton et al., 2018). Youth homelessness is especially worrying because of its damaging long-term effects (Cobb-Clark and Zhu, 2017).

We find that the RSA benefit reduces the homelessness rate by 22% among young adults ages 22 to 27 in cities with more than 20,000 inhabitants. We test our models in a subsample of respondents using a face-to-face interview, which yields substantially less ambiguity than self-administered questionnaires and allows us to control for psychological and background variables. The results are very similar to our findings using the full sample. Consistent with the assumption that free meals are an inferior good, we find a decline in the demand for (almost) free meals at food distribution centers. At the same time, respondents report an increase in the number of meals taken at home and a decrease in shelter entries.

Our results conform to a small but growing empirical literature that finds that cash assistance is associated with homelessness reduction. Evans, Sullivan, and Wallskog (2016) find that individuals who received temporary funding were 76% less likely to enter a shelter. The New Leaf project in Vancouver — an RCT in which participants received a lump sum transfer — reduced days homeless by 35%. In these programs, however, participants were surprised by the cash they received. In contrast, we study the effects of a cash transfer that can be anticipated. For the US, Parolin (2021) finds that greater access to cash transfers from the Temporary Assistance for Needy Families (TANF) is associated with declines in family homelessness. In addition to being temporary, the TANF program primarily targets single-mother families, whereas the RSA is a permanent program that covers a much broader range of poor households. Previous studies document that long-term programs are more effective

in reducing homelessness. Also in the US, using data from the Family Options Study, Gubits et al. (2018) find that access to short-term rent subsidies had almost no effect on helping homeless families achieve stable housing, whereas a permanent subsidy cut episodes of homelessness by nearly half.

Further examination helps us identify the mechanisms that drive our results. Individuals in our sample are either hosted for free, pay a partial rent, or are regular tenants. Our estimates suggest that receiving the RSA increases the probability of joining a partial-rent scheme for new RSA beneficiaries, while the effect on the probability of becoming a regular tenant kicks in only after age 26. We also find that crossing the age threshold renders individuals more likely to receive a rent subsidy and meet regularly with a case worker.

We perform a sensitivity analysis to test how changes in the definition of homelessness may impact our results and use a trimming procedure (Lee, 2009) to address potential attrition in our sample after age 25. Our core findings withstand these robustness checks. In particular, we find that the RSA benefit also reduces the probability of sleeping in places not intended for human habitation and that recidivism, measured by the number of shelter entries, declines significantly around age 26-27. Finally, we simulate the effects of extending the benefit to under-25s on the same terms that apply to 25-year-olds who are now eligible. Our findings suggest that in programs directed to homeless individuals, a substantial share of the costs would be offset by corresponding savings from the reduction in Point-in-Time (PiT) homelessness.

Our paper’s contribution to the literature is threefold. This is the first paper, to our knowledge, to empirically assess the effects of a guaranteed minimum income program on homelessness. Second, since individuals can anticipate the income from the RSA program, we study a question that is highly relevant for the implementation of cash transfer policies that aim to reduce homelessness. Lastly, the cohort we focus has great relevance. The young adult cohort is overrepresented among the 5% most costly homeless individuals in France and the US (Nationale, 2011; LAHSA, 2017).

The paper is structured as follows: Section 2 describes the RSA program. Section 3 presents and explains the data. We describe the methodology and RD results in Section 4, and conduct robustness checks in Section 5. Section 6 presents our simulations, and Section 7 concludes.

## 2 The RSA Program

The RSA, France’s largest cash transfer program, covers about 2 million households. To be eligible, a person must be at least 25 years old, residing in France, and not in school. There is no age requirement for persons with custody of at least one child, and the benefit is not conditional on training or active job search. Households with labor income whose resources fall below a certain threshold are entitled to the RSA Activity program which acts as supplementary income. Beneficiaries who accept a low-paid job may combine their salary and up to 62% of the RSA benefit, with no time limit.

The RSA benefit is scaled up according to the number of children in the household and recipients are allowed to combine the benefit with housing subsidies. The exit point for total monthly resources is €1,425 (U\$1,880) for a single person and €2,210 (U\$3,000) for a couple with 2 children.<sup>1</sup> That means that a single individual is no longer eligible for the RSA program if the cumulative amount of their last 3 salaries is greater than 3 months of RSA allowance, or €1,425 (U\$1,880).

The population of RSA recipients consists of 40% single men, 20% single women, 23% single parents, 4% childless couples, and 13% couples with children. Almost 60% of recipients are under 35. Given that young workers often do not have enough contribution periods to receive unemployment benefits, it is no surprise that the core group of RSA recipients are young single adults (Bargain and Doorley, 2011). To enroll in the program, individuals have to complete a form with information on their household’s current and past earnings. The declaration must be filed every 3 months, and access to the RSA is conditional on a means test that uses total household resources ( $Y$ ) 3 months before the application, after taxes and other benefits, according to the formula:

$$RSA = G(n) - t * (Y - D) \tag{1}$$

where the maximum benefit obtained,  $G$ , is relative to household size  $n$ ,  $t$  is the rate at which the benefit is reduced as earned and unearned income ( $Y$ ) increases, and the level and sources of income that are excluded ( $D$ ) from benefit determination. Resources

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<sup>1</sup>In 2012, a childless individual received €475 (U\$630) as the RSA benefit — 44% of the minimum wage — while a person with one child received €710 (U\$940).

also comprise other benefits, except for housing subsidies, which are deducted as a lump sum from the maximum amount  $G(n)$ . The benefit is scaled up depending on the family's composition, and so is the deduction. For RSA recipients who have just taken a job, it is possible to combine 62% ( $t = 38\%$ ) of labor earnings and the RSA without time limit. For the unemployed or individuals with income less than €500 (U\$660), the program includes an "insertion contract" in which recipients are obliged to seek professional and social support to facilitate their integration, mostly through employment. A case worker is responsible for each contract and meets the recipient on a regular basis to prioritize objectives (e.g., vocational guidance). Sanctions for non-compliance, although possible, are rarely issued (Terracol, 2009).

Since 2010, the RSA has been extended to people under 25 without children. To qualify, applicants must prove 2 years of full-time work during the 3 years preceding the application (3,214 hours). This activity condition is very restrictive, since this cohort faces the highest unemployment rates in France; In 2012, only 9,500 households were enrolled in the Young RSA program. Foreigners must be in the country legally, and different rules apply for Europeans and non-Europeans. Europeans must prove they have worked in France and be unemployed, on sick leave, or enrolled in vocational training at the time of the application. Non-Europeans should have at least a 5-year permit to work or legally reside in France. None of these conditions apply to refugees, who are eligible for RSA benefits.

RSA recipients paying rent are automatically entitled to housing benefits. In 2013, 80% of households that benefited from the RSA received a housing subsidy (Bozio, Fack, et al., 2015). The other 20% were owners, who are not eligible for the benefit. The rent subsidy for year  $n$  is determined by the household's taxable income of year  $n - 2$ , gross rent price, household composition, and geographic location.<sup>2</sup> There are three noncumulative housing subsidies. One covers registered dwellings whose owner agrees to rent to low-income tenants in exchange for tax deductions, and the other two cover accommodations not under agreement and particular cases (e.g., disabled dependent). The majority of registered dwellings are managed by low-cost housing organizations, and the money is transferred directly to the landlord. In 2012, the average monthly housing subsidy came to €220 (U\$296) per family. Most beneficiaries live alone and are tenants, and 30% are under age 30.

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<sup>2</sup>See Bozio, Guillot, et al. (2017) for the complete formula for housing benefits.



## 3 Data

### 3.1 Survey at Accommodation and Meal Distribution Centers

Our RD analysis is based on a survey conducted by the National Institute for Statistics and Economic Studies (INSEE) and the National Institute for Demographic Studies (INED) among the population using accommodation and/or meal distribution services in metropolitan France (cities of more than 20,000 inhabitants) during 2 winter months in 2012. The data are a single cross-section of users of services such as soup kitchens and shelters — a population that is usually not captured by regular surveys.<sup>3</sup>

The sample was selected in 3 stages: first, the cities were selected. Then the service sites were chosen from an exhaustive list provided by the selected cities. Lastly, the people interviewed in these sites were randomly selected. French-speaking individuals (50% of respondents) answered a face to face 1-hour interview, and non-Francophones were given a shorter, self-administered questionnaire that was available in 14 foreign languages. The survey provides detailed characteristics of the respondent and their family, such as nationality, education, and marital status. It also collects specific information on the respondent’s housing situation, employment, mental health, income, financial situation, and social benefits.

It is important to note that nearly half of the individuals in our sample who use an accommodation and/or meal distribution service are not homeless. They are owners, tenants or living with a third party such as a friend, family member, acquaintance, or association. According to the INSEE, a person is “homeless” on a given day if the previous night they used an accommodation service (shelter) or if they slept in a place not intended for habitation: street, parking lot, caravans, etc. This definition is consistent with the definition of homelessness used by the US Department of Housing and Urban Development and has not changed for more than a decade in France.<sup>4</sup>

The INSEE reports the housing status of respondents, based on where they slept the night before the survey. We denote non-homeless status with an indicator for owners or tenants, people in transitional housing programs (homeless in housing) and people who live at their parents’ or relatives’ house or squat. All others are considered to be homeless.<sup>5</sup>

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<sup>3</sup>See Ardilly and Le Blanc (2001) for a complete methodological overview of the survey.

<sup>4</sup>Federal Register/Vol. 76, No. 233/Monday, December 5, 2011/Rules and Regulations.

<sup>5</sup>See **Table A1** in the Appendix.

For French speakers, the count variable for shelter entries comes from the question, “Where have you spent the last 7 nights?” For individuals who responded to the self-administered questionnaire we used the question, “During the last 7 nights, how many times have you slept in a place provided by social services or an association?”

In order to access social assistance, especially cash programs such as the RSA, individuals need a postal address in France. The homeless usually obtain one with the help of a communal social center or an approved non-governmental organization (NGO). They can receive mail and be eligible for rights and benefits. The fact that the application process for the RSA is only possible if the applicant has access to a postal address may trigger concern that individuals seek permanent housing in order to apply for the benefit rather than receipt of the benefit causing them to find accommodation. We provide evidence that rules out this possibility at ages near the eligibility cutoff.

Using data from the National Family Allowances Office (*Caisse nationale des allocations familiales*, CNAF), the body responsible for such payments, we estimate between 75,000 and 115,000 homeless recipients of the RSA, or 4% to 6% of RSA beneficiaries. To assess the completeness of the survey, we use sampling weights to compare CNAF figures with the number of RSA recipients in our survey. We find that 30,700 individuals in our sample receive the RSA benefit, which represents coverage of 27% to 41% of the total homeless population receiving the RSA benefit, according to the CNAF in 2012.

One of the shortcomings of these surveys is that they fail to cover certain types of homeless. For example, victims of domestic violence who are forced to spend the night on the street but return to their home are not counted. The survey also does not reach homeless people who do not use free accommodation and meal distribution services (Ardilly and Le Blanc, 2001). Since that population’s size is unknown, one assumption is that all people in the homeless population used one of these services at least once during the survey reference period. According to the INSEE, the population not covered during the 2 full winter months is negligible.

To obtain the largest possible sample for our main analysis, we select all women and men aged 22 to 27. Our final sample contains to 1,499 observations from the self-administered and face-to-face questionnaires. They are representative of 15,711 adults who used accommodation and meal distribution services in metropolitan France in 2012. Moreover, we take

advantage of more detailed information from the face-to-face interviews, which include background and psychological variables, to provide additional estimations with the inclusion of these control variables. Young adults are the core group of the RSA (60%) and a large fraction of the homeless population. By keeping people with dependent children in our sample, we still observe a sharp discontinuity at age 25 without losing many observations, which renders our tests statistically more powerful. We also discuss fertility issues and how they could threaten our empirical strategy (Section 5.5).

The first two columns of **Table 1** report sample means for the full sample and the sample of individuals age 22 to 27. Panel A reports the means for all individuals and Panel B focuses on the face-to-face interviews. As can be seen by comparing the two columns, the 22-27 sample contains more women, singles, and foreigners than the full sample of individuals. In the last two columns, we report the estimated discontinuities in baseline covariates for the 22-27 sample and the associated standard errors. These estimates indicate that there is no systematic sorting of individuals on one side of the threshold. The estimated discontinuities are small and, with the exception of nationality, marital status, and having a dependent child, are statistically indistinguishable from zero.

## 3.2 Graphical Analysis

Before presenting our results, we provide a graphic assessment of the data. **Figure 1** shows the probability of receiving the RSA for individuals in our sample. The jump between ages 24 and 25 is expected to be larger in our data than for the general population. Chareyron and Domingues (2018) estimate that 17% of homeless persons are eligible but do not claim the RSA benefit, compared with 35% for the general population. In addition, this discontinuity is unique, since there are no other discontinuities in policies at age 25 in France (Bargain and Doorley, 2011). We also see that homelessness and the number of reported meals at distribution centers drops at age 25, when people become eligible for the RSA. The decline in shelter entries is smoother for observations near the discontinuity. We believe this result is because higher recidivism is observed in individuals at age 25. We discuss this further in Section 5.4. Finally, **Figure 2** displays a covariates balance check. Results are consistent with the figures in **Table 1**.

## 4 Empirical Approach

### 4.1 Regression Discontinuity (RD) Design

We use a regression discontinuity design (RD) to assess the age discontinuity in the RSA program generated by the age eligibility criterion at the age of 25. In particular, we use an indicator for age greater or equal to 25 as an instrumental variable for RSA receipt in models that control for flexible functions of age. By comparing individuals who are barely eligible and barely ineligible for the RSA based on their age, we can identify a causal impact. More formally, we estimate the following reduced-form and first-stage equations:

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 X_i + \beta_3 Age_i + \beta_4 T_i \times Age_i + \epsilon_i \quad (2)$$

$$D_i = \alpha_0 + \alpha_1 T_i + \alpha_2 X_i + \beta_3 Age_i + \beta_4 T_i \times Age_i + u_i \quad (3)$$

Where  $Y_i$  represents a given outcome (e.g., homeless status) for the  $i$ th individual,  $D_i$  denotes the probability of RSA receipt,  $Age_i$  is age centered at 25,  $X_i$  is a set of covariates, and  $T_i = \mathbf{1}[Age_i \geq 25]$ . Provided that  $T_i$  and  $\epsilon_i$  are orthogonal,  $T_i$  is a valid instrument for  $D_i$ . The identification assumption is that crossing the age threshold at 25 affects homeless status only by changing the likelihood of participating in the RSA program. We interact the centered age polynomial ( $Age_i$ ) with the  $T_i$  indicator to allow the slope of the age profile to vary on either side of the age threshold (Lee and Card, 2008).

The fuzzy RD estimator ( $\beta_1$ ) is an estimate of the causal effect of the RSA program on the given outcome  $Y_i$ . We estimate our models via OLS when the outcome variable is binary and report the marginal effects of a Poisson model when  $Y_i$  is a count variable (e.g., number of meals). Baseline covariates are dummy variables for nationality, having a dependent child, high school diploma, gender, marital and employment status, and living in the Paris area.

We use quadratic and cubic splines as parametric functions of the forcing variable. We also cluster standard errors on distinct values of age, assuming there is a group structure within each age cell, which conventional standard errors ignore (Abadie et al., 2017). It is important to emphasize that we do not see anyone turning 25. We are comparing people on both sides of the cutoff (e.g., 23- and 24-year-olds with 25- and 26-year-olds).

## 4.2 Results

We now present our main RD estimates of the impact of the minimum income program on the population of users of accommodation and meal distribution services in metropolitan France. In our tables, each column in each panel displays two coefficients for a given outcome variable, and the rows indicate the degree of the polynomials we use to model our running variable.  $\beta_0$  displays the value at the age threshold for each variable of interest in a reduced-form model (Equation 2) using a quadratic age polynomial. **Table 2** reports the estimated treatment effect of the French guaranteed minimum income program (RSA) on 3 outcomes: the probability of being homeless, the number of meals taken at meal distribution centers, and the number of entries in a shelter during the week prior to the survey date. **Figure 1** suggests that homelessness trends up just before the age cutoff and declines after the age of 25, once childless individuals become eligible for the RSA.

Panel A reports estimations using the smallest age range, 23-26, and Panel B presents estimations using a larger bandwidth comprising people aged 22 to 27. Taking into account that some of the RSA effects may take time to kick in, we present estimations using people aged 23 to 27 but excluding those at age 25. Column (1) of **Table 2** reports coefficients of about 25 percentage points in the probability of RSA receipt compared with a baseline mean of 21% among young adults just above the age threshold at ages 22-27. This result is consistent with the visual evidence also presented in Figure 1. Baseline covariates are important stabilizers due to the heterogeneity of our sample. Models with baseline covariates are more precisely estimated, since the covariates absorb part of the variation in the outcome measures (Lee and Card, 2008).

Columns (2) and (3) suggest that receiving the RSA reduces the probability of homelessness by 30-33 percentage points among young adults at ages 23 to 26. A stronger effect in the probability of being homeless is expected for observations in the smallest age band, for two reasons. First, 25-year-olds are more recent RSA beneficiaries and represent a larger share of this age group. Therefore, if the assumption that an income shock causes people to exit homelessness is correct, we would see a greater impact around this age. In addition, the sensitivity of housing status to an income shock is expected to decline with time.

Results from the models in which we use a bandwidth of  $\pm 2$  years, comprising individuals from ages 22 to 27, are reported in Panel B. The preferred estimates are the ones using cubic

splines, which are more flexible in capturing nonlinearities in the age profile. In Panel C, we present estimates of the  $\pm 1$  year age window, but we drop individuals age 25. Overall, these results are very similar to estimations using the  $\pm 2$  years bandwidth, which put less weight on 25-year-olds, and indicate a treatment effect of 19 percentage points.

The meal services offer 3 meals a day, and our estimates indicate that individuals reduce the number of meals taken at these services once they become eligible for the cash benefit. Despite the little we know about the utilization pattern of meal services, this finding is consistent with the hypothesis that these (almost) free meals are an inferior good. Moreover, these estimations inform how changes in eligibility for the RSA affect the likelihood of being in the survey, since receiving a meal distribution service is one of the main factors that determine whether an individual is observed in the data. Therefore, the estimations support the assumption that our results represent a lower bound for the estimated treatment effect.

Columns (6) and (7) report estimates for the impact of the RSA program on the number of entries in homeless shelters during the week before the survey date. Estimates across age bands indicate that individuals who receive the RSA benefit report a moderate decline in their use of shelters. The effect's magnitude is consistent with results found elsewhere in the literature and are not much affected by the inclusion of baseline covariates (Evans, Sullivan, and Wallskog, 2016).

Overall, these results conform to the idea that the income shock from the RSA program may help individuals buy better food, move to a safer place, and rely less on emergency shelters or meal distribution services. We use psychological and background information to further test the robustness of these findings.

### 4.3 The Face-to-Face Interviews

We take advantage of the wealth of information coming from the face-to-face interviews to provide additional estimates of the models presented in the last section, while controlling for psychological and background variables. According to the INSEE, these interviews contain considerably less ambiguity than the self-administered questionnaires.

**Table 3** displays the results of our models for the sample of individuals who responded to face-to-face interviews. Coefficients for homelessness and shelter entries are barely sensitive to the inclusion of psychological and background covariates, which indicates that these

unobserved characteristics were not driving our previous results. For reported meals at meal distribution centers, however, coefficients are larger than using the full sample. In addition to the set of covariates used in **Table 2**, we now we include indicators for depression, being raised by both parents, having sleeping problems, being a victim of aggression, and having a record of alcoholism in the family.

Results are very similar to the estimated effect of the RSA on the probability of homelessness reported in **Table 2**, and indicate a strong effect of 30 percentage points at the  $\pm 1$  year age range. Again, the estimated impact at  $\pm 2$  years bandwidth using cubic splines is identical to the one found when dropping individuals age 25 in the  $\pm 1$  year age window, of 13.5 percentage points. There are two interpretations for these large differences between the 23-26 age group and the other age ranges. One is that the greater impact is due to the large share of very recent RSA beneficiaries in the 23-26 age group, as mentioned before. Another is that the larger data support, using ages 22-27, allow our functional forms to better capture the relationship between treatment and outcome. A conservative approach suggests the latter, which indicates an estimated treatment effect of 14 percentage points (22%) on the probability of homelessness around the age of 25.

The effect of the RSA program on the usage of meal services is now larger than using the full sample, but these models confirm that receiving the RSA negatively affects the frequency of using meal services. These larger coefficients may reflect some differences in the sample composition of the group answering the face-to-face interview. These individuals are more likely to be single, employed, French, and have a high school diploma, compared with those who answered the self-administered questionnaire.<sup>6</sup>

Overall, estimations for the subsample of respondents who answered the face-to-face interview confirm our previous findings regarding the impact of the RSA on the probability of homelessness and the use of hot meal distribution services, with a much larger treatment effect on the latter. We also find a smaller effect on the usage of shelters, which is only significant in models that attribute less weight to 25-year-olds.

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<sup>6</sup>See **Table A4** in the Appendix.

## 4.4 Mechanisms: How does the RSA affect homelessness?

An established literature shows that unexpected changes in circumstances (e.g., adverse health shock, rent increase, job loss, etc.) among people facing housing insecurity may precipitate homelessness (O’Flaherty, 2009; Curtis et al., 2013).

Income shocks are considered to be the most important precipitating factor for homelessness and may be worsened by a conjunction of unfortunate conditions, especially when structural and individual factors coincide (O’Flaherty, 1996). Income support may act as a buffer to some of these adverse circumstances and prevent a long homeless spell. Moreover, to exit homelessness an individual or a family must pay fixed costs : costs for moving expenses, furniture, security deposit, etc. This means that someone with positive income could be trapped in homelessness even though they would have remained housed if that was their initial condition (O’Flaherty, 2012). Therefore, a positive income shock constitutes a natural channel that links the RSA program to homelessness prevention.

However, homelessness is not exclusively related to monetary poverty, so it is plausible that the effects of a positive income shock would eventually fade or be clouded by other factors. In this exercise, we quantify the additional income attributed to the RSA program. Then, we analyze the potential mechanisms behind homelessness prevention after age 25.

Consistent with the visual evidence presented in **Figure 3**, columns (1) and (2) in **Table 4** report our estimates for the effect of the RSA program on participants’ income. Our models with control variables estimate precisely the average additional income from participation in the program.<sup>7</sup> The value of the RSA benefit in 2012 was €475 (U\$630) for a single person without dependent children and €710 (U\$940) for a person with one dependent child. The results in Panel C of **Table 4**, however, indicate that this income effect is greater at age 25 and show no statistically significant differences in income among RSA beneficiaries.

Our estimates suggest that the RSA increases the probability of paying a partial rent by 30-34 percentage points across the  $\pm 1$  year and  $\pm 2$  years bandwidth, but the treatment effect is no longer significant once we drop individuals age 25. We also observe that the RSA impact on the probability of being a tenant is negative and significant in Panel A. This result is explained by the fact that stable housing through regular tenancy does not increase significantly at age 25. Instead, it starts after age 26, which causes the regression to slope

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<sup>7</sup>The sample’s median income is 450 euros.



downward for the  $\pm 1$  year age bandwidth.

In Panel C, the effect changes sign and the coefficient, of 8 percentage points, confirms that the RSA’s effect on paying a regular rent takes some time to kick in. In our sample, most of the people paying partial rent pay a fee (*participation*) to an association, organization or the landlord in order to access a private accommodation. Therefore, our results indicate that the RSA induces permanent housing first by relying on a social association or third party (family, friends, acquaintances) or doubling up in a partial-rent scheme and later achieving regular tenancy. The impact on the probability of regular tenancy is also confirmed in the full sample (with all questionnaires) for this same age range, but the coefficients are slightly smaller at 4-5 percentage points.

Finally, we find that the RSA benefit significantly increases the number of meals taken at home among individuals near the age threshold. In particular, we notice that the effect is concentrated on dinners, while the increment in the number of lunches at home is less pronounced. The stronger adjustment in meals taken at night is consistent with the fact that, in some of these rent schemes, the individual must leave the location in the morning and return by the end of the day.

## 4.5 Rents and Housing Subsidy

We find robust evidence that receiving the RSA increases the probability of joining a partial-rent scheme and induces regular tenancy at ages 26 and 27. If that is true, and the additional income from the RSA program induces permanent housing, one would expect the average rent to increase around age 25. We can further test this assumption using information on rents for individuals who responded to the face-to-face interview. **Figure 4** confirms that gross rent (net rent + housing subsidy) increases, while net rent grows by a smaller amount once individuals become eligible for the RSA benefit. Landlords and/or co-occupants receive gross rent, tenants pay net rent.

Columns (1) and (2) of **Table 5** report that net rent increases by €95-127 (U\$126-168) and gross rent by €205-250 (U\$270-330). On average, around 20% of the additional income from program participation is allocated to rents in presumably better and safer accommodations. This figure is very similar to the findings from the The New Leaf RCT in Vancouver. As previously stated, the gap between gross and net rent suggests that the

housing allowance is considerably affected by the RSA take-up in our sample. In column (4) of **Table 5**, we see that the probability of receiving a housing subsidy increases right after individuals cross the age threshold at age 25. This result could raise concern that the housing allowance might be a competing mechanism that pushes individuals out of homelessness instead of the RSA program. The data do not support this assertion.

In column (5), we use the age threshold as an instrument for the housing allowance, instead of the RSA benefit, on a sample without RSA beneficiaries.<sup>8</sup> If the impact on homelessness comes from the housing allowance and not from the RSA benefit, we would see negative and significant coefficients for these models. Instead, our results indicate there is no effect of the housing subsidy by itself. Positive and significant coefficients in column (5) of Panel C are due to the loss of density on the right side of the cutoff once we drop RSA recipients.<sup>9</sup> For this reason, the first-stage of these estimations is negative. Since receiving the housing benefit requires the payment of rent, the effect runs from the RSA to the allowance much more than the other way around. To further test this assertion, we exclude housing allowance recipients (around 10% of the sample) and test our models again. Column (6) reports our results. Coefficients are now marginally smaller than in our previous estimations, but are still negative and statistically significant.

In column (3) we report estimates of the impact of the RSA on the probability of having met a case worker in the past six months. Unemployed individuals or those whose income falls below the €500 threshold must have follow up meetings with a case worker. The case worker offers guidance on health-related issues, job and accommodation seeking, as well as information on other social benefits. We see that crossing the age cutoff increases the probability of regularly meeting with a case worker, which we believe is an additional pathway through which the RSA program would affect homelessness. Although this mechanism proves more difficult to test empirically, anecdotal evidence supports the idea that the take-up of the RSA benefit also acts as an information shock that facilitates entrance in and navigation of the generous, but somewhat complex, French welfare system. These results conform to other studies that have found larger effects of housing support among users who received other types of assistance for a longer period (Gubits et al., 2018).

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<sup>8</sup>RSA beneficiaries represent nearly 25% of the 22-27 sample.

<sup>9</sup>See Figure A2 in the Appendix.

## 5 Heterogeneity Analysis and Robustness Checks

In this section, we use the sample with all questionnaires to report the impact of the RSA on the probability of homelessness, the use of hot meal distribution services, and the frequency of shelter usage on different subgroups of our sample. We also conduct falsification tests: first, by inspecting the group of single mothers, who are not subject to the age eligibility cutoff, and then with placebo tests using fictitious age cutoffs at ages 23 and 27. **Table 6** reports our subgroup estimates using Equation (2) and including baseline covariates.

### 5.1 Immigrants and Eligibility

The inclusion of people who are not eligible for the RSA benefit may bias our results. As previously stated, foreigners must meet different criteria to be eligible for the RSA. In the absence of information on their legal status, it is impossible to know whether they are eligible to enroll in the RSA program. We also exclude disabled persons because they are entitled to a more advantageous allowance (AAH) that cannot be combined with the RSA. Our goal here is to work with a sample of individuals we know to be eligible for the RSA and for whom we know the non-take-up rate (Chareyron and Domingues, 2018).

There is a striking difference between the take-up rate of this subgroup and that of the full sample. The coefficient for receiving the RSA is now twice as large and indicates an increase of nearly 50 percentage points in the probability of receiving the benefit once individuals turn 25. Although this group presents a lower homelessness rate (0.58), the estimated effect of the RSA benefit on the probability of homelessness is very similar to that found in **Table 2** and **Table 3**, of around 18-22 percentage points.

### 5.2 Childless Individuals and High School Dropouts

Childless individuals constitute the core group of RSA recipients and 60% of the population using meal and accommodation services in France. The coefficients suggest an estimated treatment effect of 40 percentage points when the outcome is the probability of homelessness and a nearly 50% reduction in the number of meals taken at distribution services — the highest across subgroups in this age range. These results hold to including individuals in the 22-27 age range. Enrolling in the RSA program significantly impacts the usage of shelters

for this subgroup, meaning that this subgroup is particularly responsive to the RSA benefit.

For the  $\pm 1$  year age group, the coefficient indicates an increase of 21 percentage points in the probability of receiving the RSA after turning 25. For the 22-27 age group, it falls to 10 percentage points and is not statistically significant. This result is consistent with findings by Chareyron and Domingues (2018), whereby poor and uneducated users of meal and accommodation services present a lower take-up rate of the RSA benefit. The estimated treatment effect suggests a reduction of 30 percentage points in the probability of homelessness for high school dropouts in the  $\pm 1$  year sample, but for the largest age range it is not different from zero.

### 5.3 Single Mothers and Placebo Tests

We conduct a falsification test using a group that is not subject to the age eligibility criterion: single mothers. Results show insignificant treatment effects, and hence this control group tends to confirm that the effect found in our full sample is not due to other discontinuities. We also perform placebo tests on the full sample using fictitious age cutoffs to further test the robustness of our findings. If there is no discontinuity in the probability of receiving the RSA at ages 23 or 27, we should not expect any treatment effect from the RSA on our outcomes of interest. The last row of each panel in **Table 6** displays our estimates using an age window of  $\pm 2$  years. The results indicate a divergence with the results we obtained using the discontinuity at age 25: The treatment effect was always significant for the true age cutoff, whereas for the placebo thresholds the effects are not significant.

### 5.4 Sensitivity Analysis: Homeless Definition

We provide additional estimates that examine how changes in the definition of homelessness could alter our main results. So far we have used the definition of homelessness in which all housed (*en logement*) individuals were classified as non-homeless. This classifies people in transitional housing programs as non-homeless. We now use a more restrictive definition of homelessness in which individuals in transitional housing are considered to be homeless. Moreover, since we have information on where individuals slept on the 7 nights before the survey date, we generate a new “homeless variable” based on the constancy of

sleeping in a private accommodation. This means that an individual is classified as non-homeless only if they slept more than 3 days in a private accommodation (their own housing or provided by a third party) during the week before the survey date. Finally, we use the “literal homelessness” definition as an outcome variable. This means we consider homeless only those individuals sleeping in a place not intended for habitation, such as street, parking lot, makeshift shelter, etc.

**Table 7** reports the results of our sensitivity analysis. Classifying a person in transitional housing as homeless (columns 1 and 2) does not affect our main results. Columns (3) and (4) report estimates using the more restricted version of homelessness based on constancy. Interestingly, these results indicate that recidivism, as counted by the number of nights slept outside of a private accommodation, declines at age 25 but only stabilizes at ages 26 and 27. This result is explained by the simultaneous increase in the likelihood of becoming a regular tenant. Finally, we find that the RSA effect of reducing the probability of sleeping in places not intended for human habitation is concentrated at age 25.

## 5.5 “Manipulation” Effects and Attrition

For the RD approach to yield valid estimates, the decision to have children, or living with them, must be orthogonal to the RSA benefit. An example would be if a 24-year-old decides to leave their family 3 months before turning 25 so that they can apply for the minimum income as a childless single individual. If we are in the presence of this “manipulation effect”, the fraction of single individuals with dependent children will be discontinuous around the age cutoff. **Figure A3** in the Appendix shows that the fraction of singles with dependent child is not discontinuous around the threshold. We conduct the McCrary (2008) test to formally test for the presence of manipulation. We cannot reject the null hypothesis that the density of age is the same just below and just above the discontinuity threshold.

Another concern with our main estimation results is sample selection. Even if assignment of the RSA around the age cutoff appears to be as good as random, individuals who receive the RSA after age 25 might stop using services that target the very poor and select out of the scope of the survey. That means that receiving the RSA may affect the probability that a person will even be observed in our sample. We employ a trimming procedure to bound the treatment effect, as proposed by Lee (2009), with Imbens and Manski (2004)

confidence intervals as a robustness check for potential attrition at ages 25 to 27. These confidence intervals take into account both uncertainty from potential selection bias and sampling error.

**Table A2** in the Appendix reports the results of our models using the trimming approach with and without the inclusion of covariates to tighten the bounds. Estimations show a significant lower bound of 20 percentage points of the RSA’s effect on the probability of homelessness, while the upper bound is not statistically significant. This is reassuring because it confirms the impact of RSA receipt in reducing the probability of homelessness around the age cutoff. We also confirm the negative impact on the number of meals taken at meal distribution services during the week before the survey. For entries in shelters, we find mixed results at ages near the cutoff; for ages 26 and 27, only lower bounds are statistically significant. These last results lend support to the interpretation that recidivism into homelessness declines significantly at ages 26-27.

## 6 Policy Simulations

It is intrinsically difficult to estimate the benefits of reducing homelessness — and especially the value of being housed to people who would otherwise be homeless — and very few studies have attempted to do this (Evans, Sullivan, and Wallskog, 2016). A more sensible metric is the reduction in PiT homelessness per person aided. Our RD model is used to predict counterfactual policy scenarios, and we focus on an extension of welfare programs to the under-25s. In particular, we simulate the impact of lowering the minimum eligibility age of the Base RSA to 23, 21 and 18 year old on the predicted probability of homelessness.

The estimated effect of extending the age eligibility to those under 25 depends on whether the take-up rate will be the same for ages above and below the cutoff. Younger individuals may have less information about the program and be poorer because of their limited access to social benefits. Comparison with the take-up by single parents in our dataset, who are eligible before and after age 25, indicates that these differences are not significant. Chareyron and Domingues (2018) document that the non-take-up rate and stigma costs increase with age, but their analysis excludes people younger than 25. Simulating the effects of extending the RSA to the under-25s, Bargain and Doorley (2017) assume that behavior parameters vary

continuously (e.g., linearly) with age, and find that it would reduce poverty rates without creating negative employment effects.

We estimate eligibility using income information when available and provide different scenarios for policy implementation that take into account the differential take-up rate at ages below 25. Since participation rates among French nationals and foreigners are very different and legal status information is not available, we also show results for models in which we assume that all French individuals with missing information for income are eligible for the base RSA. Finally, we show estimates in which we extrapolate a linear take-up trend to ages under 25.

Estimations in Panel A of **Table A3** show that extending eligibility to the 23-24 age group on the same terms under which 25-year-olds are eligible would reduce the predicted probability of homelessness by 2 to 5.6 percentage points. In the worst case scenario, the participation rate for this age group would more than double and over 100 households would not be homeless. These estimates tend to be more accurate, since we are using observations that are very close to the discontinuity point. We find stronger effects of extending the benefit to the 18-24 age group. In our best case take-up scenario, the probability of homelessness is cut by 6.4 percentage points. The program would then include 6,118 new participant households and withdraw nearly 1,000 households from homelessness.

Although the RSA program is not explicitly a homelessness policy, one of its declared goals is to alleviate poverty. Our findings highlight the fact that the French minimum income program successfully reduces a specific type of extreme poverty: homelessness. Young adults display a significantly higher average cost €22,000 (U\$29,000) per year compared with the usual individual cost of housing support services (€16,700 (U\$22,000)). However, the costs of extending the benefit to the entire population ages 18 to 24 are unlikely to be justified based only on its ability to reduce homelessness. According to Jelloul et al. (2018), extending eligibility to 21- or 18-year-olds would represent an additional cost of €10-16 billion (U\$13-21 billion) annually compared with the current system. Yet if these programs were specifically directed to homeless individuals, around 65% of the costs would be offset by savings from the reduction in support services for the homeless.

For countries with comparable PiT homelessness statistics, almost all have more generous safety nets than the US. According to a recent report, the number of PiT homeless people

is greater in France than in the US: 0.22% and 0.18%, respectively (OECD, 2020). Other European countries, such as Germany and Sweden, display even higher PiT homelessness rates. Why do countries with apparently generous safety nets have such a high rate of PiT homelessness? Perhaps the US does not perform so poorly in the end. Recent work documents that the US redistributes a greater fraction of national income to the bottom 50% than any European country, and other studies suggest that programs such as the Earned Income Tax Credit (EITC) and the Supplemental Nutrition Assistance Program (SNAP) also impact housing outcomes and extreme poverty (Blanchet, Chancel, and Gethin, 2022; Pilkauskas and Michelmore, 2019; Tiehen, Jolliffe, and Smeeding, 2015).

## 7 Conclusion

This paper contributes to the ongoing debate on how public policies may affect extreme poverty in high-income countries (Hoynes and Rothstein, 2019). While previous studies have tried to quantify the moral hazard effects of the RSA program, our paper examines the consumption-smoothing benefits of social insurance for an especially vulnerable population.

Our study fills a gap in the empirical literature by using exogenous variation in a minimum income program. We focus on housing status because it is an informative measure of well-being for this population. Our results confirm that the RSA reduces the probability of homelessness at ages around age 25. Our estimations indicate that RSA beneficiaries first exit homelessness to pay partial rent. Subsequently, at ages 26 and 27, the RSA increases the probability of becoming a regular tenant. Also, enrolling in the program causes a decrease in the demand for free meals at distribution centers and shelter entries. These adjustments coincide with individuals reporting having more meals at home, especially dinners.

This work has limitations that could be addressed in future research. The lack of data on month of birth renders some of our tests less powerful. Additionally, the RD design captures the immediate effect of the transferred income on homelessness, but we might expect a lagged effect because it might take time to apply and receive benefits or for those benefits to affect an individual's ability to secure housing.

Previous research has found similarities between the homeless across countries (Marpsat, 1999) and our results fit with the expectations of previous theoretical works on how perma-



ment cash assistance programs could prevent homelessness (O’Flaherty, [2012](#)). Therefore, we believe that our estimations are relevant beyond the case of France.

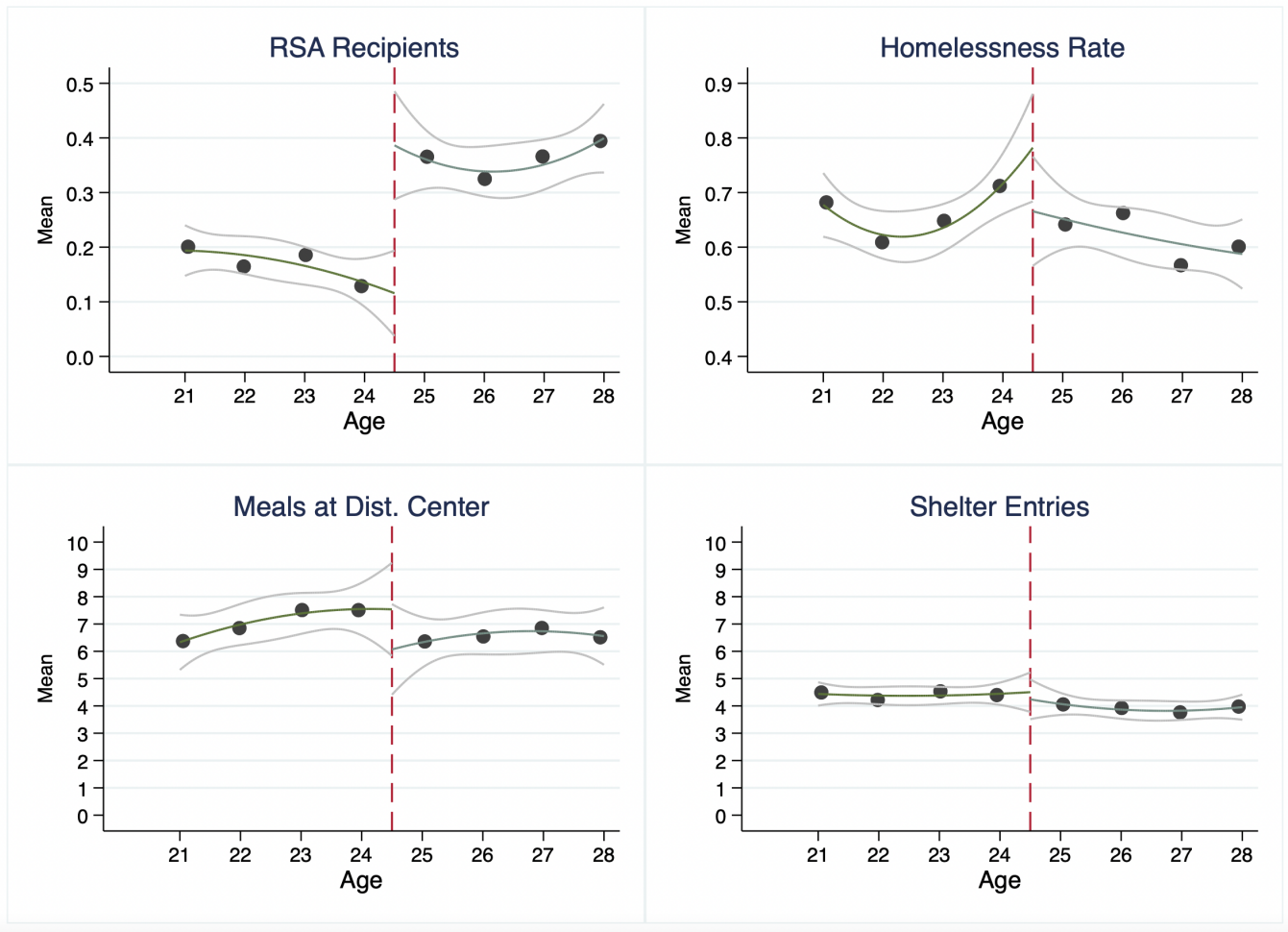
## References

- [1] Alberto Abadie et al. *When should you adjust standard errors for clustering?* Tech. rep. National Bureau of Economic Research, 2017.
- [2] Pascal Ardilly and David Le Blanc. “Sampling and weighting a survey of homeless persons: A French example.” In: *Survey Methodology* 27.1 (2001), pp. 109–118.
- [3] Olivier Bargain and Karina Doorley. “Caught in the trap? Welfare’s disincentive and the labor supply of single men.” In: *Journal of Public Economics* 95.9-10 (2011), pp. 1096–1110.
- [4] Olivier Bargain and Karina Doorley. “The Effect of Social Benefits on Youth Employment Combining Regression Discontinuity and a Behavioral Model.” In: *Journal of Human Resources* 52.4 (2017), pp. 1032–1059.
- [5] Thomas Blanchet, Lucas Chancel, and Amory Gethin. “Why Is Europe More Equal Than the United States?” In: *American Economic Journal: Applied Economics (Forthcoming)* (2022).
- [6] Antoine Bozio, Gabrielle Fack, et al. “Réformer les aides personnelles au logement.” PhD thesis. Institut des politiques publiques (IPP), 2015.
- [7] Antoine Bozio, Malka Guillot, et al. “Designing housing benefits: An application with French data.” In: *Economie Prévision* 2 (2017), pp. 163–175.
- [8] CAE. “Commission des affaires économiques du Sénat.” In: (2020).
- [9] Sylvain Chareyron and Patrick Domingues. “Take-up of social assistance benefits: The case of the French homeless.” In: *Review of Income and Wealth* 64.1 (2018), pp. 170–191.
- [10] Deborah A Cobb-Clark and Anna Zhu. “Childhood homelessness and adult employment: The role of education, incarceration, and welfare receipt.” In: *Journal of Population Economics* 30.3 (2017), pp. 893–924.
- [11] Marah A Curtis et al. “Life shocks and homelessness.” In: *Demography* 50.6 (2013), pp. 2227–2253.

- [12] William N Evans, James X Sullivan, and Melanie Wallskog. “The impact of homelessness prevention programs on homelessness.” In: *Science* 353.6300 (2016), pp. 694–699.
- [13] Daniel Gubits et al. “What interventions work best for families who experience homelessness? Impact estimates from the Family Options Study.” In: *Journal of Policy Analysis and Management* 37.4 (2018), pp. 835–866.
- [14] Kate J Hodgson et al. “Psychopathology in young people experiencing homelessness: A systematic review.” In: *American Journal of Public Health* 103.6 (2013), pp. 24–37.
- [15] Hilary Hoynes and Jesse Rothstein. “Universal basic income in the United States and advanced countries.” In: *Annual Review of Economics* 11 (2019), pp. 929–958.
- [16] Guido W Imbens and Thomas Lemieux. “Regression discontinuity designs: A guide to practice.” In: *Journal of econometrics* 142.2 (2008), pp. 615–635.
- [17] Guido W Imbens and Charles F Manski. “Confidence intervals for partially identified parameters.” In: *Econometrica* 72.6 (2004), pp. 1845–1857.
- [18] Mahdi Ben Jelloul et al. “Revenu de base: Simulations en vue d’une expérimentation.” PhD thesis. Institut des politiques publiques (IPP), 2018.
- [19] Los Angeles Homeless Services Authority LAHSA. “Data and reports.” In: (2017).
- [20] David S Lee. “Training, wages, and sample selection: Estimating sharp bounds on treatment effects”. In: *Review of Economic Studies* 76.3 (2009), pp. 1071–1102.
- [21] David S Lee and David Card. “Regression discontinuity inference with specification error.” In: *Journal of Econometrics* 142.2 (2008), pp. 655–674.
- [22] Maryse Marpsat. “Les sans domicile à Paris et aux Etats-Unis.” In: *Données Sociales, la Société Française* (1999), pp. 480–489.
- [23] Justin McCrary. “Manipulation of the running variable in the regression discontinuity design: A density test”. In: *Journal of econometrics* 142.2 (2008), pp. 698–714.
- [24] Matthew H Morton et al. “Prevalence and correlates of youth homelessness in the United States.” In: *Journal of Adolescent Health* 62.1 (2018), pp. 14–21.
- [25] Étude Nationale. “Première Étude Nationale Des Coûts du Dispositif Accueil, Hébergement, et Insertion. Ministère des Solidarités et de la Cohésion sociale”. In: (2011).

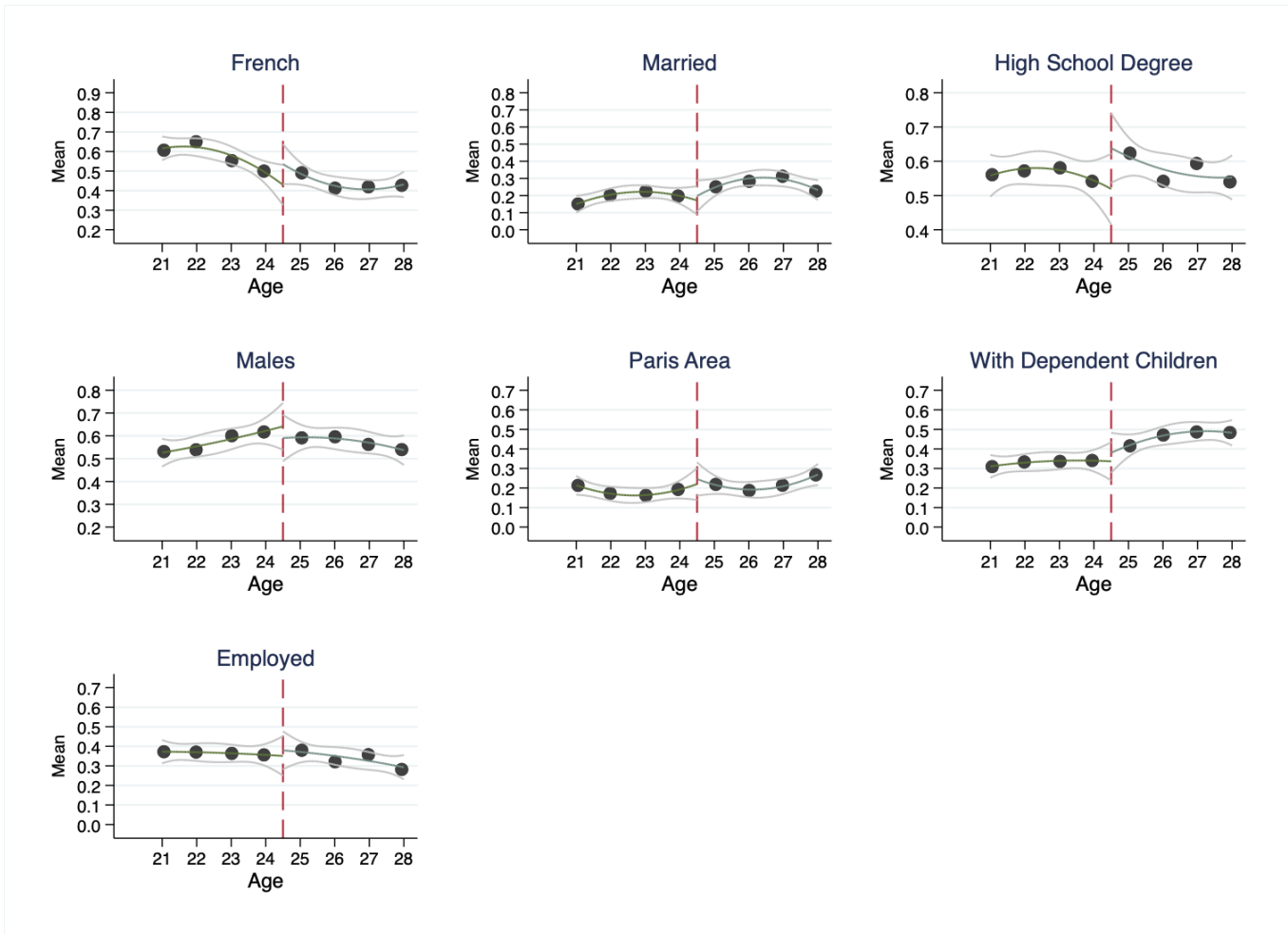
- [26] OECD. *HC3.1 homeless population. Organisation for Economic Co-operation and Development—Social Policy Division—Directorate of Employment, Labour and Social Affairs*. Tech. rep. OECD, 2020.
- [27] O’Flaherty. *Making room: The economics of homelessness*. Harvard University Press, 1996.
- [28] O’Flaherty. “What shocks precipitate homelessness?” In: *Discussion Paper No. 0809–14. New York: Department of Economics, Columbia University*. (2009).
- [29] Brendan O’Flaherty. “Homelessness research: A guide for economists (and friends).” In: *Journal of Housing Economics* 44 (2019), pp. 1–25.
- [30] Brendan O’Flaherty. “Individual homelessness: Entries, exits, and policy.” In: *Journal of Housing Economics* 21.2 (2012), pp. 77–100.
- [31] Zachary Parolin. “Income support policies and the rise of student and family homelessness.” In: *ANNALS of the American Academy of Political and Social Science* 693.1 (2021), pp. 46–63.
- [32] Natasha Pilkauskas and Katherine Micheltore. “The effect of the earned income tax credit on housing and living arrangements.” In: *Demography* 56.4 (2019), pp. 1303–1326.
- [33] Antoine Terracol. “Guaranteed minimum income and unemployment duration in France.” In: *Labour Economics* 16.2 (2009), pp. 171–182.
- [34] Laura Tiehen, Dean Jolliffe, and Timothy Smeeding. “The effect of SNAP on poverty.” In: *SNAP matters: How food stamps affect health and well-being* (2015), pp. 49–73.
- [35] USICH. “U.S. Targeted Homelessness Assistance: Discretionary Budget Authority in Millions of Dollars.” In: (2018).
- [36] Françoise Yaouancq et al. “L’hébergement des sans-domicile en 2012. Des modes d’hébergement différents selon les situations familiales.” In: *INSEE première* 1455 (2013), pp. 1–4.

**Figure 1: Outcome Variables by Age Cell**



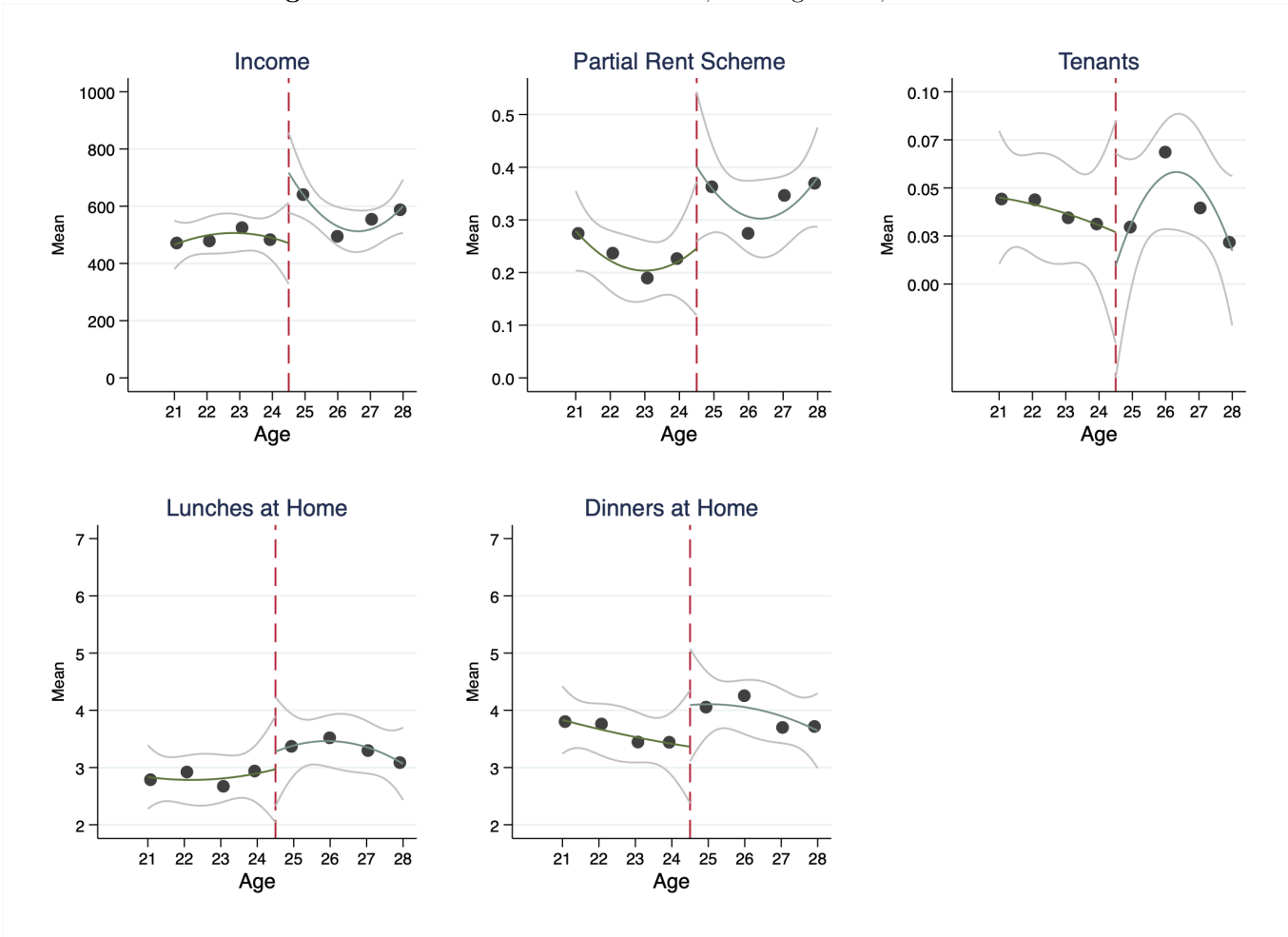
Note: This figure plots the mean by age cell and 95% confidence intervals of the following variables: RSA recipients, homelessness rate, number of meals taken at food distribution centers during the week prior to the survey and number of nights the individual slept in a shelter (*centre*) during the week prior to the survey date. The dashed line denotes the age eligibility threshold at age 25.

Figure 2: Covariate Balance Checks



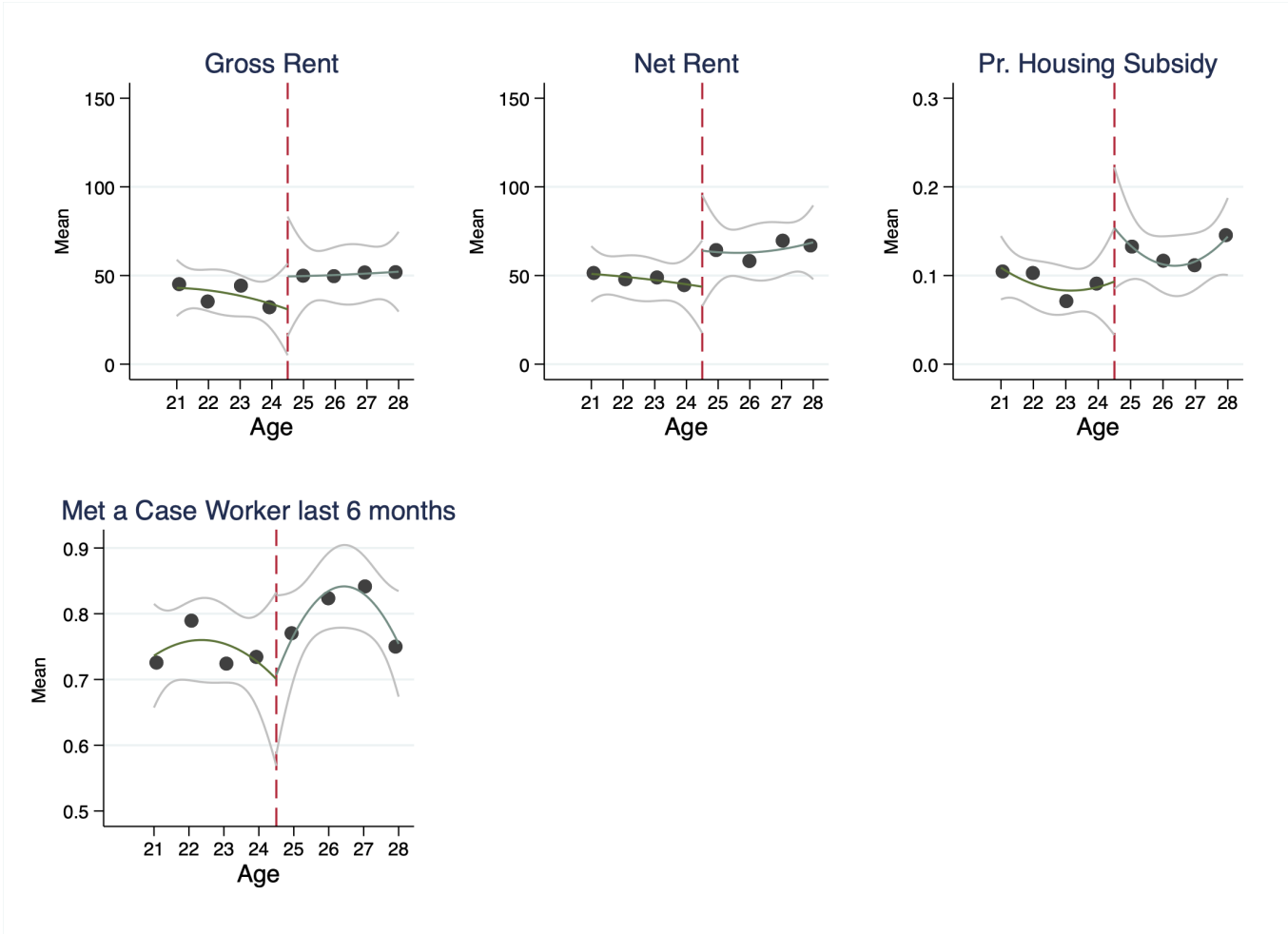
Note: This figure plots the mean by age cell and 95% confidence intervals of French, married, high school degree (*bac*), males, living in the Paris Area, and having a dependent child. The dashed line denotes the age eligibility threshold at age 25.

**Figure 3:** The effect of RSA on income, housing status, and meals at home



Note: This figure plots the mean by age cell and 95% confidence intervals of the following variables: income, pay partial rent, regular tenants, number of lunches at home during the week prior to the survey date, and number of dinners at home during the week prior to the survey date. The dashed line denotes the age eligibility threshold at age 25.

**Figure 4:** The effect of RSA on rent and housing subsidy



Note: This figure plots the mean by age cell and 95% confidence intervals of the following variables: gross rent, net rent, probability of receiving housing subsidy, and probability of having met with a case worker in the 6 months before the survey date. The dashed line denotes the age eligibility threshold at age 25.



**Table 1: Descriptive Statistics**

<b>Panel A- All Questionnaires</b>				
	<b>Full</b>	<b>22-27</b>	<b>Coeff.</b>	<b>SE</b>
Sample Size	8,733	1,499		
<i>Demographics:</i>				
Males	0.637	0.584	0.004	(0.027)
Never Married	0.619	0.703	-0.076	(0.024)
French	0.513	0.444	-0.141	(0.043)
Employed	0.326	0.328	0.025	(0.041)
Have Children	0.585	0.426	0.134	(0.028)
Paris Area	0.352	0.339	-0.014	(0.020)
Mail Box	0.543	0.566	-0.031	(0.067)
High School Diploma	0.558	0.592	0.008	(0.035)
<b>Panel B- Face-to-Face Questionnaire</b>				
Sample Size	3,906	653		
Males	0.626	0.568	-0.088	(0.061)
Never Married	0.640	0.838	-0.104	(0.031)
French	0.628	0.571	-0.222	(0.041)
Employed	0.481	0.522	0.091	(0.057)
Have Children	0.573	0.394	0.150	(0.116)
Paris Area	0.418	0.379	-0.027	(0.103)
Mail Box	0.549	0.560	-0.036	(0.092)
High School	0.648	0.724	0.020	(0.063)
Raised by Both Parents	0.618	0.535	0.098	(0.029)
Depression	0.237	0.166	0.032	(0.075)
Trouble Sleeping	0.536	0.557	0.033	(0.041)
Alcoholism in the Family	0.219	0.217	0.001	(0.045)
Victim of Aggression	0.267	0.336	0.108	(0.057)
Income	619.736	513.234	67.894	(41.101)

Note: The first two columns report the weighted mean of each variable in the full sample and in the 22-27 sample. The last two columns report estimated coefficients and clustered standard errors (by age cell) of an “over 25” dummy variable in regressions with these variables as outcomes.

**Table 2:** Impact of the RSA on Homelessness

<b>Panel A-</b> Ages 23 to 26							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Age Polynomial</i>	First-Stage	Pr. Homeless	Pr. Homeless	Meal at Dist.	Meals at Dist.	Center	Center
<i>Quadratic</i>	0.241*** (0.010)	-0.422*** (0.000)	-0.335*** (0.049)	-3.292*** (0.544)	-4.472* (2.439)	-2.491*** (0.040)	-2.342*** (0.301)
<i>Cubic</i>	0.222*** (0.010)	-0.384*** (0.000)	-0.304*** (0.048)	-3.344*** (0.534)	-4.307* (2.438)	-3.050*** (0.006)	-2.318*** (0.278)
$\beta_0$	0.216	0.659	0.659	6.133	6.173	3.901	3.913
$N$	1034	1034	1034	1,034	1,034	1,034	1,034
Controls	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>
<b>Panel B-</b> Ages 22 to 27							
<i>Quadratic</i>	0.173** (0.047)	-0.325*** (0.090)	-0.254*** (0.067)	-6.601** (2.524)	-7.155** (3.455)	-2.892*** (0.472)	-2.974*** (0.768)
<i>Cubic</i>	0.168** (0.047)	-0.254** (0.092)	-0.193** (0.061)	-5.622** (1.843)	-5.971** (2.626)	-2.744*** (0.309)	-2.774*** (0.553)
$\beta_0$	0.218	0.625	0.625	5.863	5.889	3.685	3.696
$N$	1,499	1,499	1,499	1,499	1,499	1,499	1,499
Controls	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>
<b>Panel C-</b> Ages 23 to 27 (without 25)							
<i>Quadratic</i>	0.242** (0.025)	-0.183*** (0.000)	-0.143*** (0.036)	-4.403*** (0.407)	-3.354** (1.043)	-2.048*** (0.035)	-1.770*** (0.232)
<i>Cubic</i>	0.230** (0.024)	-0.231*** (0.000)	-0.189*** (0.040)	-4.237*** (0.389)	-3.017** (0.954)	-2.448*** (0.042)	-2.153*** (0.215)
$\beta_0$	0.216	0.634	0.634	6.186	6.213	3.724	3.733
$N$	979	979	979	979	979	979	979
Controls	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>

Clustered standard errors in parentheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$ .

Note: Column 1 reports our first-stage results. In columns 2-7, we estimate the model described in Equation 2 for three outcomes: probability of being homeless, number of meals taken at distribution centers, and number of shelter entries. Baseline covariates are dummy variables for Paris area, high school diploma (*bac*), gender, dependent child, nationality, marital and employment status.  $\beta_0$  is the constant term in Equation 3 using a quadratic polynomial for age. Each coefficient is an estimate of the impact of the RSA program on the given outcome, with treatment instrumented by age eligibility.

**Table 3: Impact of the RSA on Homelessness (Face-to-Face Interviews)**

<b>Panel A- Ages 23 to 26</b>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Age Polynomial</i>	First-Stage	Pr. Homeless	Pr. Homeless	Meal at Dist.	Meals at Dist.	Center	Center
<i>Quadratic</i>	0.328*** (0.016)	-0.400*** (0.000)	-0.293** (0.106)	-6.297*** (1.457)	-14.385* (7.812)	-1.471*** (0.095)	-2.005 (1.598)
<i>Cubic</i>	0.298*** (0.017)	-0.383*** (0.000)	-0.284** (0.099)	-7.168*** (1.563)	-14.621* (7.935)	-1.669*** (0.100)	-2.004 (1.399)
$\beta_0$	0.245	0.633	0.633	6.326	6.919	3.993	4.250
<i>N</i>	453	453	453	445	445	451	451
Psychological Controls	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>
<b>Panel B- Ages 22 to 27</b>							
<i>Quadratic</i>	0.263** (0.054)	-0.347*** (0.063)	-0.151* (0.082)	-12.500** (5.258)	-17.337* (8.999)	-3.247** (1.292)	-2.710* (1.446)
<i>Cubic</i>	0.249** (0.059)	-0.325*** (0.045)	-0.134** (0.058)	-11.938** (4.956)	-16.612** (8.373)	-3.375** (1.312)	-2.832** (1.421)
$\beta_0$	0.253	0.595	0.595	5.984	6.136	3.626	3.700
<i>N</i>	653	653	653	653	653	653	653
Psychological Controls	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>
<b>Panel C- Ages 23 to 27 (without 25)</b>							
<i>Quadratic</i>	0.382** (0.039)	-0.221*** (0.000)	-0.086 (0.078)	-6.319*** (0.763)	-10.207** (4.337)	-2.536*** (0.174)	-2.787* (1.593)
<i>Cubic</i>	0.354** (0.042)	-0.280*** (0.000)	-0.135** (0.067)	-6.668*** (0.814)	-9.519** (3.723)	-2.943*** (0.193)	-2.970** (1.386)
$\beta_0$	0.243	0.598	0.598	6.680	7.151	3.705	4.006
<i>N</i>	420	420	420	413	413	417	417
Psychological Controls	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>

Clustered standard errors in parentheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$ .

Note: Estimates in column 1 report our first-stage results. In columns 2-7, we are estimating the model described in Equation 2 for three outcomes: the probability of being homeless, the number of meals taken at meal distribution centers and shelter entries.  $\beta_0$  is the constant term in Equation 3 using a quadratic polynomial for age. Estimations in columns (1), (3), (5), and (7) include the same controls as in Table 2 and we add dummy variables for depression, being raised by both parents, trouble sleeping, being a victim of aggression, and alcoholism episodes in the family.

**Table 4:** Impact of the RSA on Homelessness - Mechanisms

<b>Panel A-</b> Ages 23 to 26						
<i>Age Polynomial</i>	(1)	(2)	(3)	(4)	(5)	(6)
	Income	Income	Partial Rent	Tenant	Lunch	Dinner
<i>Quadratic</i>	156.527*** (0.000)	431.608*** (72.071)	0.336*** (0.055)	-0.087** (0.035)	5.005 (3.733)	9.023** (4.056)
<i>Cubic</i>	202.705*** (0.000)	472.217*** (74.575)	0.365*** (0.051)	-0.089** (0.031)	4.893 (3.337)	9.297** (4.166)
$\beta_0$	503.334	503.334	0.184	0.041	2.776	3.626
<i>N</i>	481	481	481	481	481	481
Controls	<b>No</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>
<b>Panel B-</b> Ages 22 to 27						
<i>Quadratic</i>	221.294* (116.627)	370.161** (125.053)	0.343** (0.154)	-0.053 (0.062)	5.593*** (1.395)	10.983*** (2.247)
<i>Cubic</i>	248.594* (136.630)	389.862** (152.917)	0.335** (0.152)	-0.043 (0.072)	4.685*** (1.195)	9.606*** (2.092)
$\beta_0$	498.885	498.885	0.204	0.051	2.928	3.792
<i>N</i>	696	696	696	696	696	696
Controls	<b>No</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>
<b>Panel C-</b> Ages 23 to 27 (without 25)						
<i>Quadratic</i>	-47.764*** (0.000)	108.487 (70.799)	0.045 (0.072)	0.083** (0.035)	1.783* (0.970)	5.048** (1.773)
<i>Cubic</i>	-2.889*** (0.000)	103.415 (79.385)	0.088 (0.065)	0.086** (0.031)	1.810** (0.912)	4.742** (1.851)
$\beta_0$	492.008	492.008	0.190	0.065	2.711	3.458
<i>N</i>	447	447	447	447	447	447
Controls	<b>No</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>

Clustered standard errors in parentheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$ .

Note: Estimates in column 1 report our first-stage results. In columns 2-7, we are estimating the reduced-form model described in Equation 2 for five outcomes: income, probability of paying partial rent, probability of paying full rent, and the number of lunches and dinners taken at home on the week before the survey. Baseline covariates are the same as in Table 2.  $\beta_0$  is the constant term in Equation 3 using a quadratic polynomial for age. Each coefficient is an estimate of the impact of the RSA program on the given outcome, with treatment instrumented by age eligibility.

**Table 5:** Impact of the RSA on Homelessness - Mechanisms II

<b>Panel A-</b> Ages 23 to 26						
<i>Age Polynomial</i>	(1)	(2)	(3)	(4)	(5)	(6)
	Gross Rent	Net Rent	Case Worker	Housing Allo.	No RSA	No Hous. Allo.
<i>Quadratic</i>	198.892*** (5.811)	102.107*** (2.296)	0.122** (0.057)	0.186*** (0.020)	19.729 (118.469)	-0.226*** (0.049)
<i>Cubic</i>	216.672*** (7.245)	111.184*** (4.304)	0.109* (0.059)	0.213*** (0.021)	-35.062 (497.851)	-0.183*** (0.042)
$\beta_0$	104.564	72.853	0.684	0.092	0.715	0.708
<i>N</i>	481	481	481	1034	773	927
Controls	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>
<b>Panel B-</b> Ages 22 to 27						
<i>Quadratic</i>	182.310** (71.504)	79.308 (49.083)	0.188*** (0.038)	0.229** (0.096)	6.166 (8.983)	-0.199*** (0.028)
<i>Cubic</i>	186.131** (71.612)	82.952* (48.400)	0.150*** (0.015)	0.244** (0.103)	8.642 (27.498)	-0.128** (0.061)
$\beta_0$	114.881	79.281	0.732	0.096	0.685	0.675
<i>N</i>	696	696	696	1499	1116	1342
Controls	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>
<b>Panel C-</b> Ages 23 to 27 (without 25)						
<i>Quadratic</i>	51.023** (18.259)	6.112 (21.656)	0.068 (0.046)	0.021** (0.010)	1.839*** (0.425)	-0.152** (0.062)
<i>Cubic</i>	82.699*** (15.289)	25.987 (19.400)	0.113** (0.051)	0.062*** (0.010)	2.232*** (0.600)	-0.195** (0.066)
$\beta_0$	115.261	80.882	0.092	0.726	0.695	0.679
<i>N</i>	447	447	979	447	738	884
Controls	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>

Clustered standard errors in parentheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$ .

Note: Columns (1) to (3) report estimations of the reduced-form model described in Equation 2 for gross rent, net rent, and probability of having met with a case worker in the last 6 months with the face-to-face sample. Column (4) shows the impact of the RSA on the probability of receiving housing subsidy on the full sample. In columns (5) and (6), the outcome variable is the probability of homelessness. In column (5), we use the age threshold as an instrument for the housing allowance on a sample without RSA beneficiaries, and in column (6) we exclude housing subsidy recipients. Baseline covariates are the same as in Table 2.  $\beta_0$  is the constant term in Equation 3 using a quadratic polynomial for age.

**Table 6:** Fuzzy RD Estimates: Subgroup Analysis

<b>Panel A-</b> Ages 23 to 26							
<i>Sub Groups</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First-Stage	Value at Thr.	Pr. Homeless	Value at Thr.	Meals at Dist.	Value at Thr.	Center
<i>Able bodied French</i>	0.493***	0.717	-0.228**	6.053	-2.272	3.885	-1.138**
<i>N = 484</i>	(0.022)		(0.070)		(1.925)		(0.483)
<i>Childless Individuals</i>	0.284***	0.771	-0.403***	7.735	-10.678***	4.179	-1.226***
<i>N = 631</i>	(0.006)		(0.028)		(2.658)		(0.174)
<i>HS Dropouts</i>	0.211***	0.828	-0.309***	6.342	5.067	4.244	-2.034
<i>N = 441</i>	(0.015)		(0.078)		(4.648)		(1.252)
<i>Single Mothers</i>	0.074	1.006	-1.583	3.660	-0.647	3.676	-22.690**
<i>N = 163</i>	(0.034)		(1.034)		(92.644)		(10.625)
<i>Placebo age 23</i>	-0.005	1.326	-12.09	6.065	-178.0	3.992	-24.96
<i>N = 1,501</i>	(0.0518)		(94.90)		(858.5)		(50.77)
Controls	<b>No</b>		<b>Yes</b>		<b>Yes</b>		<b>Yes</b>

<b>Panel B-</b> Ages 22 to 27							
<i>Able bodied French</i>	0.394**	0.587	-0.179**	5.647	-5.979**	3.641	-2.080**
<i>N = 726</i>	(0.060)		(0.068)		(3.010)		(0.684)
<i>Childless Individuals</i>	0.235***	0.707	-0.194	0.707	-12.879**	3.960	-1.713**
<i>N = 906</i>	(0.032)		(0.123)		(4.261)		(0.535)
<i>HS Dropouts</i>	0.104	0.508	0.692	6.339	14.854	4.130	-2.979
<i>N = 635</i>	(0.067)		(0.985)		(12.464)		(2.278)
<i>Single Mothers</i>	-0.072	0.273	0.371	3.811	2.433	3.453	16.083
<i>N = 248</i>	(0.075)		(1.141)		(15.412)		(19.173)
<i>Placebo age 27</i>	-0.0207	0.614	4.065	5.981	-12.27	3.645	1.434
<i>N = 1,444</i>	(0.0364)		(6.815)		(10.09)		(10.99)
Controls	<b>No</b>		<b>Yes</b>		<b>Yes</b>		<b>Yes</b>

Clustered standard errors in parentheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$ .

Note: This table reports results within different subgroups. Estimates in column 1 report our first-stage results. In columns 2-7, we are estimating the reduced-form model described in Equation 2, using a third-degree polynomial spline, for three outcomes: probability of homelessness, number of meals taken at the meal service and, number of shelter entries. Columns (2), (4), and (6) report the mean values for each outcome variable. Baseline covariates are dummy variables for Paris area, high school diploma (*bac*), gender, having a dependent child, nationality, marital and employment status.  $\beta_0$  is the constant term in Equation 3 using a cubic polynomial for age. Each coefficient is an estimate of the impact of the RSA program on the given outcome, with treatment instrumented by age eligibility.

**Table 7: Sensitivity Analysis — Alternative Definitions of Homelessness**

<b>Panel A- 23 to 26</b>						
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Age Polynomial</i>	Pr. Homeless	Pr. Homeless	Pr. Homeless I	Pr. Homeless I	Literal	Literal
<i>Quadratic</i>	-0.321*** (0.000)	-0.373*** (0.013)	-0.279*** (0.000)	-0.163 (0.108)	-0.326*** (0.000)	-0.227*** (0.045)
<i>Cubic</i>	-0.247*** (0.000)	-0.307*** (0.013)	-0.293*** (0.000)	-0.159 (0.117)	-0.250*** (0.000)	-0.158*** (0.043)
$\beta_0$	0.864	0.864	0.604	0.604	0.111	0.111
<i>N</i>	1,034	1,034	481	481	1,034	1,034
<b>Panel B- 22 to 27</b>						
<i>Quadratic</i>	-0.075 (0.176)	-0.133 (0.164)	-0.351*** (0.045)	-0.215* (0.118)	-0.030 (0.212)	0.041 (0.221)
<i>Cubic</i>	-0.003 (0.212)	-0.061 (0.202)	-0.303*** (0.067)	-0.160* (0.096)	0.070 (0.252)	0.135 (0.265)
$\beta_0$	0.842	0.842	0.600	0.600	0.109	0.109
<i>N</i>	1,499	1,499	696	696	1,499	1,499
<b>Panel C- 23 to 27 (without 25)</b>						
<i>Quadratic</i>	-0.248*** (0.000)	-0.294*** (0.014)	-0.355*** (0.000)	-0.190** (0.082)	-0.236*** (0.000)	-0.174** (0.053)
<i>Cubic</i>	-0.233*** (0.000)	-0.284*** (0.014)	-0.414*** (0.000)	-0.233** (0.077)	-0.137*** (0.000)	-0.077 (0.052)
$\beta_0$	0.841	0.841	0.604	0.604	0.119	0.119
<i>N</i>	979	979	447	447	979	979
Controls	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>

Clustered standard errors in parentheses.

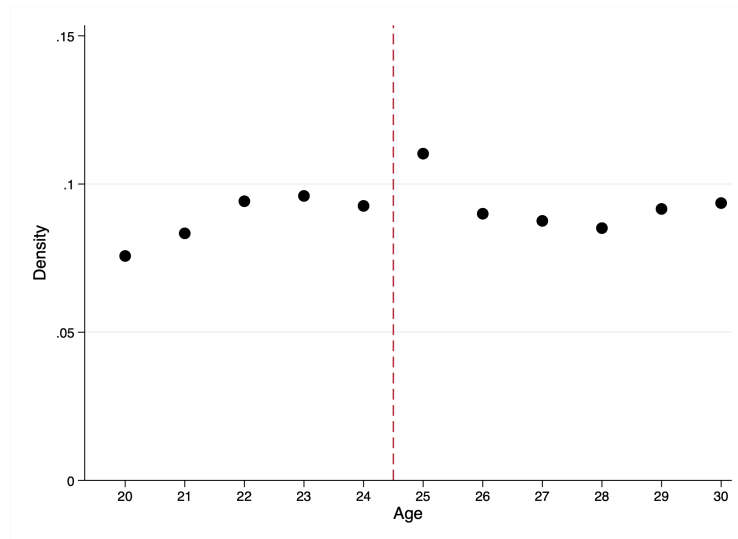
\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$ .

Note: This table displays the results in our main homeless sample. We now use different definitions of homelessness. In columns (1) and (2), we use the same definition as in our main results but consider homeless those in transitional housing programs. In columns (3) and (4), individuals are coded as non-homeless if they slept more than 4 nights in a private accommodation during the week prior to the survey. Columns (5) and (6) display models with literal homelessness as the outcome variable. Estimates with control variables are displayed in columns (2), (4), and (6).  $\beta_0$  is the constant term in Equation 3 using a quadratic polynomial for age. Baseline covariates are dummy variables for high school diploma (*bac*), gender, having a dependent child, nationality, marital and employment status. Each coefficient is an estimate of the impact of the RSA program on the given outcome, with treatment instrumented by age eligibility.



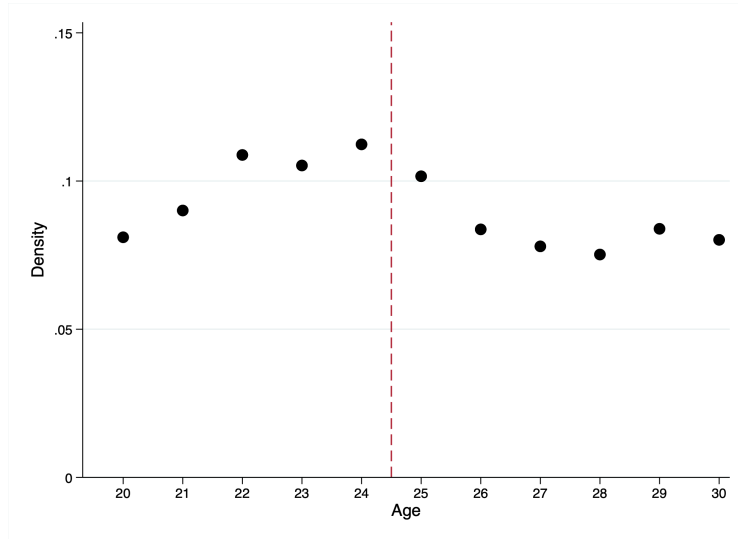
## 8 Online Appendix (For Online Publication)

**Figure A1:** Density of Forcing Variable (Age)



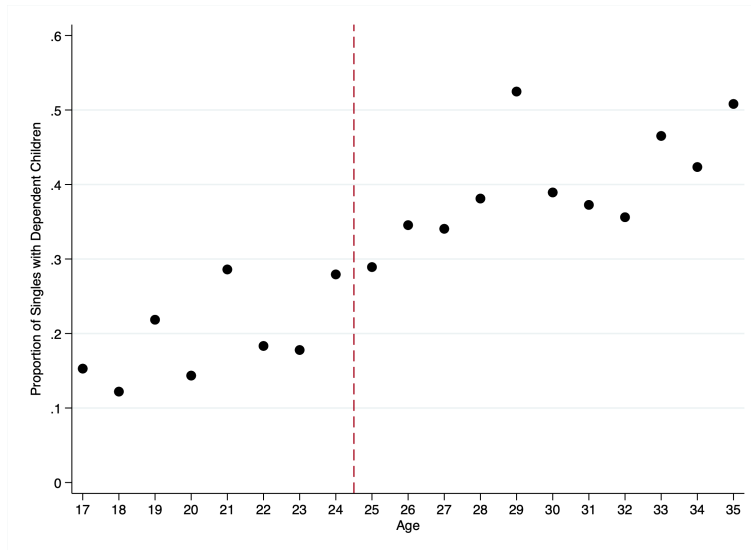
Note: This figure shows the density of the forcing variable age. The dashed line denotes the age eligibility threshold at age 25.

**Figure A2:** Density by Age Cell (Excluding RSA Recipients)



Note: In Figure A2, we display age density between ages 20 and 30 in the INSEE and INED surveys without RSA recipients.

**Figure A3:** Proportion of Singles with a Dependent Child by Age Cell



Note: In Figure A3, we display the proportion of single individuals with a dependent child between ages 17 and 35 in the INSEE and INED surveys. We perform the McCrary (2008) test and fail to reject the null hypothesis of discontinuity in the density function of the running variable around the cutoff (p-value = 0.640).

**Table A1:** Housing Status — INSEE and INED Surveys

<b>Non-Homeless</b>	<b>Homeless</b>
LPA = other collective housing in the field	SDH = homeless in hotel
SDL = homeless in housing (transitional)	SDR = homeless in the street
LOC = tenants or owners	SDCQ = leaves the center in the morning during the week
LPS = people in squats	SDCR = stays in the center but not in a dormitory
LPT = housed by a third party	SDCD = stays in the evening in a room or dormitory
LCA = people in caravans	
LPH = people paying for a hotel	

Note: This table displays housing status categories in the INSEE and INED surveys for users of meal and accommodation services in metropolitan France in 2012.

**Table A2:** Results Using the Trimming Approach

<b>Panel A- 23 to 26</b>						
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Lee Bounds</i>	Pr. Homeless	Pr. Homeless	Meal at Dist.	Meal at Dist.	Center	Center
<i>Lower Bound</i>	-0.548*** (0.073)	-0.202** (0.069)	-5.583*** (0.458)	-2.285 (1.779)	-3.294*** (0.482)	-0.676 (0.531)
<i>Upper Bound</i>	0.007 (0.078)	0.028 (0.085)	1.707* (0.998)	1.243 (1.355)	0.709 (0.533)	1.307** (0.524)
Trimming Proportion	0.356	0.356	0.375	0.375	0.381	0.381
<i>N</i>	1,034	1,034	1,034	1,034	1,034	1,034
<b>Panel B- 22 to 27</b>						
<i>Lower Bound</i>	-0.647*** (0.050)	-0.349*** (0.081)	-5.650*** (0.440)	-3.283*** (0.939)	-3.467*** (0.298)	-1.581** (0.564)
<i>Upper Bound</i>	-0.052 (0.056)	-0.004 (0.097)	2.074** (0.947)	2.448** (1.108)	0.748* (0.418)	1.039** (0.514)
Trimming Proportion	0.373	0.373	0.390	0.390	0.394	0.394
<i>N</i>	1,499	1,499	1,499	1,499	1,499	1,499
<b>Panel C- 23 to 27 (without 25)</b>						
<i>Lower Bound</i>	-0.646*** (0.055)	-0.324*** (0.080)	-5.984*** (0.469)	-3.102*** (0.892)	-3.510*** (0.291)	-1.395** (0.573)
<i>Upper Bound</i>	-0.009 (0.077)	-0.008 (0.097)	1.683 (1.131)	1.734 (1.289)	0.799 (0.547)	0.814 (0.580)
Trimming Proportion	0.389	0.389	0.405	0.405	0.415	0.415
<i>N</i>	979	979	979	979	979	979
Controls	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>	<b>No</b>	<b>Yes</b>

Clustered standard errors in parentheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$ .

Note: This table replicates the results from Table 3 using Lee's bounded treatment effects (Lee, 2009). Imbens and Manski (2004) confidence intervals capture both uncertainty about selection bias and the sampling error. In columns 1-6, we are estimating the reduced-form model described in Equation 2 for three outcomes: probability of being homeless, number of meals taken at meal distribution centers and number of times the individual slept in a shelter. In Panel A, our estimations are confined to the age group 23-26, Panel B show estimates within the  $\pm 2$  year bandwidth, and Panel C shows estimates without age 25. In estimates in columns (2), (4), and (6) we use baseline covariates to tighten the bounds. Baseline covariates are dummy variables for gender, having a dependent child, and nationality.

**Table A3: Policy Simulations****Panel A-** Eligibility at age 23 (Participation 23-24 = 0.126)

Take-up	Participation	New Beneficiaries	$\Delta\%$ p(Homeless)	PiT Homeless Reduction
Same take-up as 25-27	0.280	798	-2.0	103
Linear Trend	0.314	976	-2.6	135
Chareyron and Domingues (2018)	0.359	1,210	-3.4	177
Full take-up	0.367	1,252	-3.5	182
Full take-up (imputation for French)	0.490	1,890	-5.6	291

**Panel B-** Eligibility at age 21 (Participation 21-24 = 0.139)

Take-up	Participation	New Beneficiaries	$\Delta\%$ p(Homeless)	PiT Homeless Reduction
Same take-up as 25-27	0.299	1,616	-1.9	191
Linear Trend	0.332	1,950	-2.4	240
Chareyron and Domingues (2018)	0.377	2,403	-3.0	306
Full take-up	0.386	2,495	-3.2	320
Full take-up (imputation for French)	0.525	3,888	-5.3	523

**Panel C-** Eligibility at age 18 (Participation 18-24 = 0.145)

Take-up	Participation	New Beneficiaries	$\Delta\%$ p(Homeless)	PiT Homeless Reduction
Same take-up as 25-27	0.319	2,608	-2.6	398
Linear Trend	0.328	2,805	-2.7	420
Chareyron and Domingues (2018)	0.396	3,857	-3.9	600
Full take-up	0.407	4,012	-4.1	627
Full take-up (imputation for French)	0.544	6,118	-6.4	988

Note: Simulations use coefficient values from regression (3) in Panel B in **Table 2**. Columns display take-up assumption, average participation rate, number of new beneficiaries, change in homelessness in percentage points, and PiT reduction of homeless households. The rows in each Panel show the take-up rate assumption as in Chareyron and Domingues (2018) using income information, full take-up based on income eligibility, full take-up assuming all French with missing information for income are eligible, the same take-up as observed in the 25-27 age group, and the estimated take-up using a linear trend.

**Table A4:** Descriptive Statistics across Questionnaires

<b>Panel A- All Questionnaires</b>				
	<b>Face-to-Face</b>	<b>Self-Adm</b>	<b>Coeff.</b>	<b>SE</b>
Sample Size	8,733	1,499		
<i>Demographics:</i>				
Males	0.554	0.612	-0.074	(0.063)
Never Married	0.828	0.597	0.230***	(0.031)
French	0.543	0.367	0.203***	(0.042)
Employed	0.518	0.179	0.344***	(0.041)
Have Children	0.416	0.432	0.003	(0.056)
Paris Area	0.374	0.321	0.035	(0.051)
Mail Box	0.559	0.715	-0.155***	(0.038)
High School	0.726	0.484	0.234***	(0.029)
Hospitalized	0.332	0.291	0.039	(0.037)
Lives Alone	0.757	0.742	0.026	(0.048)

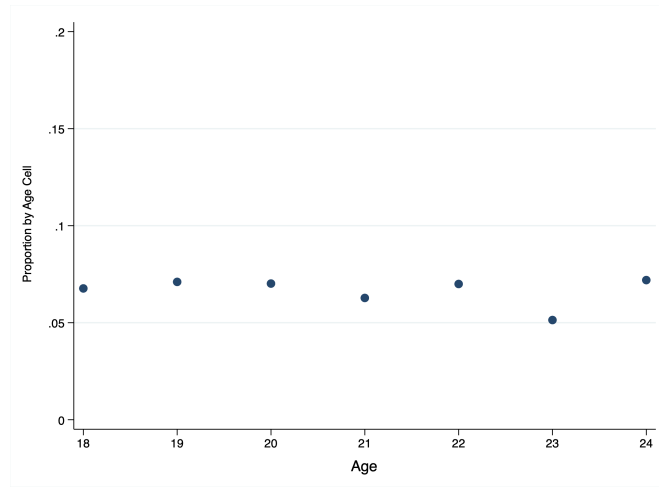
Note: The first two columns report the weighted means of each variable in the face-to-face sample and in the self-administered questionnaire sample. Last two columns report estimated coefficients and clustered standard errors (by age cell) of a “Face-to-Face Interview” dummy variable in regressions with these variables as outcomes.

## 8.1 Do people anticipate the RSA benefit?

An important issue is the extent to which 23- and 24-year-olds anticipate receipt of the minimum income (RSA) on their 25th birthday or soon thereafter. It is plausible to assume that they could anticipate it and, as we know from macro, people treat surprise income differently from anticipated income. The lack of data makes it hard to fully address this question. Bargain and Doorley (2011) find a significant decrease in the proportion of short-term contracts at age 25 which suggests that younger workers take transient jobs while “waiting” to join the program. In a later study, however, the authors argue that the disincentive effects were removed by the 2009 reform (Bargain and Doorley, 2017).

**Figure A4** displays the proportion of people who tried to obtain the RSA benefit from ages 18 to 24. We would expect the number of claimants to increase near age 25 if people anticipate the RSA benefit. However, these very vulnerable individuals may have imperfect knowledge of their eligibility for the RSA benefit.

**Figure A4:** Proportion of people with rejected claims for the RSA benefit by age cell



Note: This figure displays the proportion of people with rejected claims for the RSA benefit by age cell.