Does Social Interaction Matter for Welfare Participation?

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Abstract:

We estimate neighbourhood peer effects on income support participation in France. Taking into account residential migrations of recipients and public housing assignment, we use strategies that tackle common bias in the identification of social interaction effects on welfare participation. Furthermore, we investigate heterogeneity of the neighbourhood peer effects. Our results highlight that neighbourhood composition has a significant and positive effect on the participation of individuals living in that neighbourhood.

Keywords: neighbourhood effects, social interactions, welfare participation

JEL Code: H55; I38; D62

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Section 1: Introduction

One of the key issue regarding social programs is linked with the non-take-up puzzle (Frick and Groh-Samberg, 2007). This phenomenon is described in the literature as the fact that a portion of eligible persons for social assistance either do not claim it or do not receive it. This result has been highlighted by studies in different contexts (Currie, 2006) and among all the explanations, two main mechanisms emerged from the literature. The first is that eligible people suffer from a lack of information about how to take-up the social support (McGarry 1996; Tempelman and Houkes-Hommes 2016). The second is that people are affected by a stigma associated with the claim (Moffitt, 1983). Following these explanations, the neighbourhood composition may substantially impact the take-up rate since it affects both information availability and the level of stigma. In this paper we investigate how social interactions affect the take-up of social benefits, using data from the French Labour Force Survey (LFS), from 2003 to 2014.

To define social interaction, we follow the typology of Manski (2000) that describes apparent social interactions as the result of three different phenomena: contextual interactions (when an individual's behaviour varies with the group's exogenous characteristics), endogenous interactions (when an individual's behaviour is influenced by the group's behaviour) or correlated effects (when an individual's behaviour is similar to their neighbours' because they have the same characteristics or institutional environment). Following this canonical paper, only the two first phenomena which characterise the influence of the social environment, while the correlated effects can lead to correlated behaviours across groups of peers even if there is no social interaction effect. Therefore, the main challenge is to distinguish the causal effect of social interactions from the correlated effects.

The effect of social networks and information spillovers from the neighbourhood have been highlighted to induce a substantial effect on different aspects of individual behaviours such as educational attainment (Goux and Maurin, 2007), teenage childbearing (Crane, 1991), criminal activities (Glaeser, Sacerdote and Scheinkman, 1996) or human capital acquisition (Borjas, 1995). Regarding the literature about the effect of social interactions on welfare participation, previous studies have provided some evidence. Papers such as Åslund and Fredriksson (2009), Aizer and Currie (2004), as well as Bertrand, Luttmer, and Mullainathan (2000) show a substantial positive effect of knowledge spillovers among ethnic minorities on the use of social programs. More recently, Anne and Chareyron (2017) also suggest potential information sharing between households regarding their participation in a program that allows free public transportation. Nevertheless other papers such as Bettinger, Long, Oreopoulos, and Sanbonmatsu (2012) and Katz, Kling, and Liebman (2001) conclude to a non-significant effect of the quality of the neighbourhood in welfare participation.

A potential explanation for these different results relies on the complexity of distinguishing between social interactions and correlated effects. For instance, even a randomised assignation of individuals to different neighbourhoods does not distinguish between these two effects, since this strategy can address the sorting issue but not the neighbourhood‘s characteristics, such as the number of welfare offices. To overcome this issue, a few studies have used an instrumental variable (IV) strategy. For instance, Rege, Telle, and Votruba (2012) use plant-downsizing events as an IV to investigate how the neighbourhood affects participation in disability pension program. Shang (2013) uses the variation in welfare benefits and neighbourhood demographic composition to distinguish between endogenous neighbourhood effects and the effects of neighbourhood characteristics. These two studies show that social interactions play a substantial role in welfare participation.

Toward the same aims, Gibbons, Silva, and Weinhardt (2013) offer an alternative strategy for disentangling social interactions and correlated effects. These authors investigate how neighbourhood peer composition affects children’s educational attainment considering the sorting issue, the reflection problem and the omitted variables issue at the individual and neighbourhood levels. This strategy relies on a difference-in-differences estimation, in which the treatment is a change in the characteristics of neighbourhood peers. This research design captures directly the impact of residential movers on individuals who do not move, to identify the causal effects of neighbourhood composition. The authors found no significant effect of changes in the neighbourhood on teenage educational attainment. However, this empirical strategy could be implemented to investigate how social interactions affect the participation in a welfare program.

Unlike investigations on educational performance, a particular problem arises when analysing neighbourhood effects on welfare participation: some individuals may not be eligible for social programs. In this case, the social interaction effect could be downward biased, since it can affect only a limited proportion of neighbourhood’s population. This issue has not been considered by most of the studies. Therefore, in this paper, we propose further analysis of this topic. In this way, we build on a strategy used by Goux and Maurin (2007) to investigate how the neighbourhood affects the educational outcome, and by Sari (2012) who analyses the effect of being located in a deprived neighbourhood on unemployment. This strategy relies on public housing assignments that result in a quasi-exogenous distribution of individuals. More precisely, the administrative authorities of public housing have little control over the area in which the dwelling is located and individuals have even less control over the area in which their housing will be located. This situation theoretically makes the public housing assignment of the families more exogenous than in the private sector, enabling the identification of social interaction effects and limiting the selection issue. We add to this strategy a finite mixture model estimation that allows the population to be divided between individuals who are likely to be eligible and those who are not.

This paper contributes to the existing literature about the effect of social interactions on welfare participation, using two approaches to tackle two important shortcomings in the literature about social interaction effects and welfare participation. More precisely, in the first step, we regress the variation in the number of individuals participating in a social program in a neighbourhood for one year and half on the participation rate of individuals who stay in this same geographical area during that period. Furthermore, in the second step, we compare the results provided by this strategy with those found by an identification strategy based on the public housing assignment (Goux and Maurin, 2007) combined to a finite mixture model to account for the individuals' eligibility. Finally, we discuss the two methods' advantages and the drawbacks of the two methods. Using these two strategies, we identify significant positive social interaction effects in welfare program participation. We also find some heterogeneity depending on individual and neighbourhood characteristics. We believe that this research design represents the most suitable way of distinguishing social interactions and correlated effects to investigate how neighbourhood peers affect the participation in welfare programs.

The next section discusses our data and the French social context. Section 3 describes our first empirical strategy, and section 4 presents descriptive statistics and our main results as well as potential heterogeneous effects. We provide some robustness tests in section 5. Then, we consider the potential eligibility bias through an alternative empirical strategy based on the public housing assignment in section 6. Section 7 concludes.

Section 2: Data and social context

Data

To investigate the effect of social interactions on the individual participation in social programs, we used data from 12 waves of the LFS conducted in France, each year by the *Institut National de la Statistique et des Etudes Economiques* (INSEE) (from 2003 to 2014). This survey is designed to collect both quarterly and annual information on individuals over 15 years of age living within various groups of approximatively 20 adjacent households, which are defined as a neighbourhood unit. More specifically, this survey includes data for 26,064 neighbourhood units. Each inhabitant of households belonging to these units are interviewed every three months during a period of one year and half (under the condition that the household stays in the same neighbourhood unit during this period). Data recorded in the survey are multipurpose.

Hence, this survey collects information on gender, date and place of birth, nationality, family composition, labour market situation, and educational level. It also provides data about respondent's participation in social programs. This topic is only investigated during the first and the last of the six interviews. Therefore, using this survey can allow to identify the net entry of individuals in a particular neighbourhood unit during a period of six interviews. On average, more than 23% of the initial population in a neighbourhood unit is renewed before the end of the interview period. After restricting our population to those who live in the same neighbourhood unit from the first to the last interview (defined as "the stayers"), the data contain 411,705 individuals living in 19,924 different neighbourhoods. Combining this information, we can evaluate the effect of the net entry of newcomers on the participation in social programs of individuals who stay in the same unit over the period. Since neighbourhoods have on average approximately 30 inhabitants, a neighbourhood unit is composed of a small population of individuals. This fact means we are focusing on small groups of individuals close to each other.

Social context

The French welfare system displays a diversity of mean-tested welfare programs. One of the most important of these programs is the income support program, *Revenu de Solidarité Active*. This income support program is designed to sustain low-income households and to facilitate both their professional and social integration. Moreover, it is managed by the *départements*[1] and must to be claimed by eligible individuals. Claimants must declare their financial resources and provide information upon which entitlement is calculated. A declaration form must be completed, updated, and filed every three months. Consequently, some eligible people either do not claim or do not receive it. This phenomenon, defined as a non-take-up of social benefit, is substantial in this program.

A number of studies have shown the prevalence of this phenomenon on the income support program (Chareyron and Domingues, 2016; Domingo and Pucci, 2014). Thus, receipt

[1] In France, a *département* is an administrative unit that can be thought of as a county. There are 101 *départements* with an average population of about 660,000 inhabitants.

of these programs may depend on the level of information owned by the individuals and stigma suffered (Moffitt, 1983). Since, both the level of information and the stigma may be influenced by the neighbours, we expect that participation in the income support program is potentially affected by social interactions.

Section 3: Empirical strategy

The identification of a proper effect of social interactions requires the differentiation of social interactions from correlated effects. To this aim, as the first step, we use a reverse engineering approach proposed by Moffitt (2001) and applied by Gibbons *et al*. (2013) on educational outcomes. This method consists of studying changes in the outcome of the stayers receiving new individuals in the neighbourhoods. For these stayers, all neighbourhood characteristics remain the same over the time, except the neighbourhood composition, which is affected by the newcomers. Therefore, this approach controls for neighbourhood characteristics, such as factors affecting local perception and information about welfare programs (information campaigns, distance to the administration, etc…). That identifies separately the effects arising from changes in neighbourhood composition, which Gibbons *et al*. (2013) call "neighbourhood peer effects".[2]

In our case, we exploit changes in neighbourhood compositions induced by migration to estimate the effects of these changes on stayers' participation in the welfare program. Thereby, the estimated coefficient related to social interactions will not be affected by the characteristics which are specific to the neighbourhood, but only by the peer composition. To estimate the model, we use a change-in-change design. The reduced-form of the linear relation between an individual decision to participate in a welfare program and peers' characteristics in the neighbourhood, other than neighbourhood infrastructures and individual characteristics is:

$$y_{inct} = z_{nct}\beta + x_i'y + x_i'\delta t + \varepsilon_{inpct}$$

where y_{inct} denotes the outcome of individual *i* living in neighbourhood *n*, belonging to birth cohort *c*, and interviewed in year *t*. The outcomes will be the participation in the French income support program previously mentioned. z_{nct} is measuring neighbourhood peer composition, and x_i' contains individual observable characteristics with a potential time-trending effect captured by δt. The error term is assumed to be:

[2] Note that the estimated coefficient does not represent what Manski (2000) calls endogenous interactions, because the effects of neighbours' behaviour are not separately identified from the effects of the neighbours' characteristics that give rise to those behaviours.

$$\varepsilon_{inpct} = \alpha_i + \phi_n + \vartheta_{ct} + \tau_{pt} + \xi_n t + e_{inpct}$$

where α_i represents an unobserved individual-level fixed effect that captures all constant personal and family background characteristics. ϕ_n represents unobserved neighbourhood characteristics and $\xi_n t$ represents unobserved trending factors of the *département,* such as gentrification dynamics or asymmetric cyclical shocks. ϑ_{ct} is a cohort specific shock, and τ_{pt} is a specific shock of the panel wave which may capture variation in welfare perception or information that is common to individuals belonging to the same cohort on the same panel wave. e_{inpct} is assumed to be uncorrelated with the right-hand side variables, but endogeneity issues arise because the components α_i, ϕ_n, $\vartheta_{ct}, \xi_n t$, and τ_{pt} are potentially correlated with z_{nct} and x_i'.

To eliminate the unobserved components that could jointly determine peer neighbour composition and individual participation in the income support program, we take within-individual differences between the first and the last interviews:

$$(y_{inc1} - y_{inc0}) = (z_{nc1} - z_{nc0})\beta + x_i'\delta + (e_{inpc1} - e_{inpc0})$$

where the subscripts t=0 and t=1 indicate the first and last interviews. The sample is restricted to the individuals who stay in the neighbourhood from the first to the last interview and $(z_{nc1} - z_{nc0})$ only depends on the inflows and outflows of movers who are not in the estimation sample. The error term is now:

$$\left(e_{inpc1} - e_{inpc0}\right) = \xi_n + (\vartheta_{c1} - \vartheta_{c0}) + (\tau_{p1} - \tau_{p0}) + \upsilon_{inpct}$$

The difference eliminates the individual and the neighbourhood unobserved components that are fixed over time. υ_{inct} is assumed to be a random component. The specification does not control for changes in welfare perception $(\vartheta_{pc1} - \vartheta_{pc0})$ for individuals belonging to a given cohort and to a given panel wave $(\tau_{p1} - \tau_{p0})$. These terms are possibly non-zero, because of perception variations during the life cycle and the year concerned. We thus include a cohort and panel-wave fixed effect to absorb this source of variation.

Section 4: Results

Panel A of the table A1 in Appendix summarises the main variables for individuals who do not move (defined as the stayers). Approximately 1% of the stayers receive the income support allowance analysed in this paper. Panel B of this table presents the means and standard deviations of the changes in neighbourhood's composition during the year and half of the observation.

Table 1 presents the results on the relationship between variations of the neighbourhood composition and receipt of the income support for the stayers. Column (1) presents results from a regression that does not includes any control variable, column (2) reproduces this estimation including a *département* trend and column (3) adds, to the previous specification, cohort dummies and the panel fixed effects. Then, columns (4), (5) and (6) reproduce the strategy presented in the first three columns but including control variables capturing individual's characteristics. We add each individual's nationality, matrimonial status, educational level, employment status, net wage, and gender as well as the number of children under 18 living in the household, the size of the urban area where the individual is living, and whether the neighbourhood belongs to a sensitive urban area (SUA).[3]

Table 1: Neighbourhood composition and general participation in the welfare program

	Panel A: No control			Panel B: With controls		
VARIABLES	(1) In receipt of the income support	(2) In receipt of the income support	(3) In receipt of the income support	(4) In receipt of the income support	(5) In receipt of the income support	(6) In receipt of the income support
Net entry of recipients in the Neighbourhood	0.00477*** (0.000786)	0.00478*** (0.000787)	0.00392*** (0.000736)	0.00477*** (0.000800)	0.00480*** (0.000801)	0.00392*** (0.000748)
Controls	NO	NO	NO	YES	YES	YES
Cohort fixed effect	NO	NO	YES	NO	NO	YES
Panel fixed effect	NO	NO	YES	NO	NO	YES
Département fixed effect	NO	YES	YES	NO	YES	YES
Observations	411,696	411,696	411,696	399,462	399,462	399,462
R-squared	0.001	0.001	0.007	0.002	0.003	0.009

*Notes: *, **, *** represent significance at 1%, 5%, and 10% level, respectively. Standard errors clustered at the neighbourhood level in parentheses. Number of observations: approximately 400,000 in approximately 20,000 neighbourhoods. Control variables: each individual's nationality, matrimonial status, educational level, number of children under 18, size of the urban area, whether the neighbourhood belongs to a Sensitive Urban Area, net wage, gender and employment status.*
Source: French Labour Force Survey from 2003 to 2014.

The overall result from Table 1 is that the arrival of a recipient, who participates in the French income support, in a neighbourhood, increases the probability of individuals, living in this same place, of receiving the income support. When we compare results from panels A and panel B in Table 1, we see that individual controls do not affect substantially the

[3] Until 2015, a sensitive urban area (SUA) was an area inside a city that was designated to be affected in priority by state public policy because of its socio-economic characteristics. There were 751 SUAs in France before 2015.

estimated coefficient accounting for the neighbourhood effect. Nevertheless, our estimated coefficients are substantially smaller when we control for cohort and panel fixed effects (columns 3 and 6). Moreover, since the R-squared is higher for Column 6, we select this specification for our interpretations. This result indicates that the arrival of a new beneficiary in a neighbourhood increases in mean by approximately 0.4 percentage points the probability that individuals, living in this neighbourhood, will receive the income support.

We now investigate heterogeneity in neighbourhood peer effects depending on individual and neighbourhood characteristics. Table 2 explores heterogeneity in individuals' response to neighbourhood changes according to whether the individual is male or female (columns (1a)-(1b)), whether the individual has at least one child under 18 or not (columns (2a)-(2b)), and whether the individual lives as single or as a couple (columns (3a)-(3b)). The results show that some heterogeneity exists among the different subpopulations. The arrival of a new recipient in a neighbourhood increases more (in a mean by approximately 0.5 percentage points against 0.3) the probability that a "stayer" will receive the income support if this "stayer" is a female rather than a man, has at least one child under 18 years old instead of having no child under 18, and is a single person rather than a person in couple.

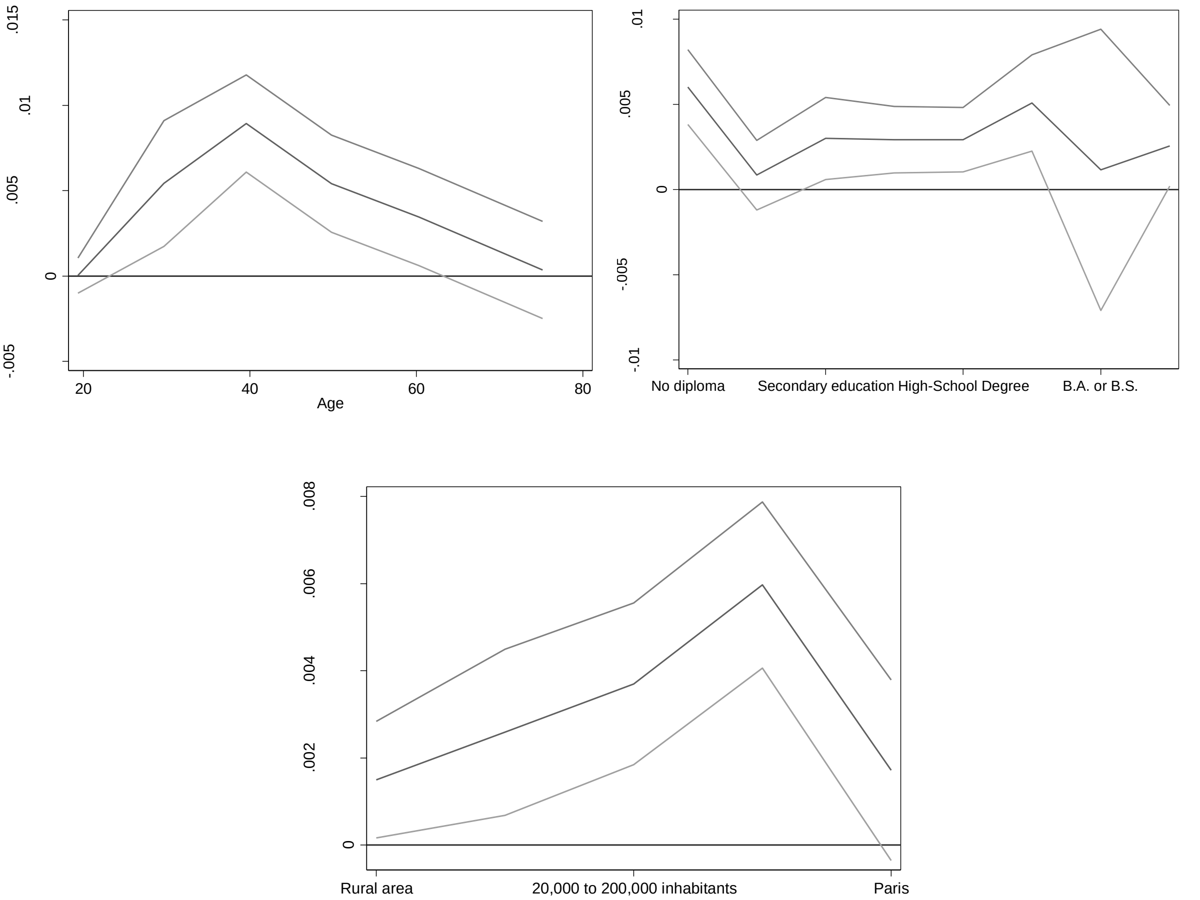
Table 2: Heterogeneity in neighbourhood effects by individual and neighbourhood characteristics.

	Dependent variable is: in receipt of one of the allowance					
VARIABLES	(1a) Female	(1b) Male	(2a) No child under 18	(2b) At least one child under 18	(3a) Single	(3b) Couple
Net entry of recipients	0.00486***	0.00274***	0.00299***	0.00534***	0.00470***	0.00268***
	(0.000984)	(0.000844)	(0.000650)	(0.00136)	(0.000968)	(0.000923)
Number of observations	212,385	187,077	258,943	140,519	185,241	214,221

*Notes: *, **, *** represent significance at 1%, 5%, and 10% level, respectively. Standard errors clustered at the neighbourhood level in parentheses. Marginal effects are estimated by running the regressions on the different subpopulations. Control variables: each individual's nationality, matrimonial status, educational level, number of children under 18, size of the urban area, whether the neighbourhood belongs to a Sensitive Urban Area, net wage, gender and employment status.*
Source: French Labour Force Survey from 2003 to 2014.

Graphics presented in Figure 1 also investigate the heterogeneity in neighbourhood peer effects for the variables age, educational level and size of the urban area. While the effect appears to have no substantial heterogeneity depending on the educational level, the social interaction effect is stronger for individuals around 40 years of age and individuals living in medium cities. The neighbourhood effect is significant at 10 % for individuals who are between 25 and 60 years old, and for all those who are not living in the metropolitan Paris area.

Figure 1: Heterogeneity of the effect depending on the age, the educational level, and the size of the urban area.



Notes: B.A. and B.S. mean Bachelor of Art and Bachelor of Science, respectively. Average marginal effects and confidence intervals at the 90% level are presented. Marginal effects are estimated by running the regressions on the different subpopulations. For instance, the marginal effect in the metropolitan Paris area is estimated while conducting the regression on the subpopulation of individuals living in the metropolitan Paris area.
Source: French Labour Force Survey from 2003 to 2014.

Section 5: Robustness checks

The validity of our identification strategy relies on the assumption that changes in the neighbour-peer composition are not linked to the unobserved characteristics of individuals who stay in the neighbourhood, nor to the other unobservable characteristics of the neighbourhoods. We consider as individual and neighbourhood characteristics: gender, age, educational level, whether the individual is employed, nationality (EU 15 member), marital status (whether the household lives as a couple), individual net wage, size of the urban area and whether the neighbourhood belongs to a SUA.

To confirm that changes in neighbourhood-peer composition are not strongly linked to an individuals' background or a neighbourhood characteristic, we carry out regressions of these characteristics on the neighbourhood changes in participation at the neighbourhood-level.[4] Results derived from these regressions are reported in Table 3. The main result is that nearly all the estimated coefficients are not significant. This result supports our identification strategy since the treatment variable could be reasonably considered as random once we partial out individual and neighbourhood-fixed effects. Therefore our estimates of Tables 1 and 2 are not biased by individual and neighbourhood unobservable characteristics, since Altonji, Elder, and Taber (2005) indicate that the correlation of neighbour-peer changes with observable characteristics is linked to the degree of correlation with the unobservable characteristics.

Table 3: Balancing of changes in neighbourhood characteristics

	(1)
VARIABLES	Net entry of income support recipients
Individual is male	0.379
	(0.591)
Age	0.00321
	(0.00366)
Education	-0.00562
	(0.0332)
Individual is	-0.162
Employed	(0.197)
UE 15 member	0.182
	(0.492)
Household living as a couple	-0.305*
	(0.182)
Net wage	7.21e-05
	(7.11e-05)
Urbanization of the neighbourhood	0.0967**
	(0.0477)
Sensitive Urban Area	-0.0565
	(0.1832)

*Notes: The table reports coefficients and robust standard errors from regressions of one of the dependent variable on the net entry of income support recipients in the neighbourhood. *, **, *** represent significance at 1%, 5%, and 10% level, respectively.*
Source: French Labour Force Survey from 2003 to 2014.

Nevertheless, a potential weakness could occur if unobserved shocks, conditional on cohort, panel wave or *département* trends, affect simultaneously the welfare participation and the distribution of characteristics of residential movers. In other words, a bias could be induced by families who move in response to neighbourhood shocks that affect welfare

[4] The regressions include no other control variables and we do not use controls for cohort and panel wave effects in these balancing tests, they are included in Tables 1 and 2.

participation. Evidence from the 2012 French Housing Survey (HS) provides, however, little support for the idea that residential migration occurs as a result of neighbourhood shocks. This nationally representative survey provides information on the housing conditions. In particular, this survey investigates the reasons why households have moved during the 4 past years. According to Table A2 of the Appendix, the main explanations are: i) tenure status change (16%); ii) dwelling size (14%) and home accessibility (10%); iii) partnership formation (10%) and dissolution (9%). Neighbourhood-specific reasons (such as: disliking the area, noise, safety or way of life) are specified by 4% of the households who have moved in the past four years.[5] Consequently, there is little reason to believe that our results are biased by neighbourhood shocks that directly affect welfare participation and induce changes in neighbour-peer composition.

Section 6: Identification using the public housing assignment

As a second step to highlight the effects of neighbourhood peers on income support participation, we use the public housing assignment. This strategy allows the obtaining of a quasi-exogenous distribution of individuals, enabling the identification of neighbourhood effects and limiting the selection issue (Goux and Maurin 2007; Sari 2012).

Public housing is managed by many institutions and eligible households usually apply simultaneously for different housings. Each household must file a record for the public housing application with a registration number. The file is unique in the *départements* where there is a shared application file. Housing is eventually awarded under certain conditions: limited financial resources set according to the household's composition or the location of the desired housing, regularity of the stay, and priority of the person with disabilities, financial difficulties, hosted, victims of violence, to name only a few.

However, the public housing demands is annually much higher than the available housings. According to the French social union for habitat (USH), applications for housing not provided in 2014 were estimated to be 1.8 million. The waiting list is long, and a household is likely to wait several years before getting housing: according to the 2013 housing survey, 29% of households in public housing, at the time of the investigation, had waited for more than a year before getting a housing; 49% of those who filed a claim had been waiting for more than 1 year. This high level of demand is due to the lower housing rents compared to those in the private sector. In 2014, in large cities, the average monthly rent of

[5] The conclusion is broadly the same for a subpopulation of households who have received the income support during the 12 past months: less than 5% give a neighborhood-specific reason to explain their move.

tenants in the social sector was two times lower than tenants in the private sector (USH, 2015). This situation leads to a very low housing turnover, sustaining the higher demand for public housing.

Thus, public housing's administrative authorities offer a reduced number of housing and have little control over the area in which the dwelling is located; the families have even less control. This situation theoretically makes the public housing assignment of the families more exogenous than in the private sector. If this assumption is true, the benefit of social income by a person in a public housing neighbourhood should not be strongly linked to the proportion of beneficiaries in the area, ex ante (at least within the given geographic area and once taken into account some observable characteristics that can influence the category of the public housing requested). Our estimate of households living in public housing should then help to limit the potential influence of unobservable characteristics.

Thanks to the French LFS, we have information on the occupancy status to identify neighbourhoods that only comprise public housing. In Table 4, after restricting our sample to the information about each neighbourhood's first interview, we have 53,484 people living in neighbourhoods composed only of public housing, and 628,101 individuals living in areas that are not exclusively composed of public housing. In public housing neighbourhoods, 4,953 newcomers and 48,531 individuals have occupied the neighbourhood for more than one year.[6]

Table 4: Types of neighbourhood and seniority

	Public housing	Non-public housing	Total
New residents	4,953	56,417	61,370
Residents for more than one year	48,531	571,684	620,215
Total	53,484	628,101	681,585

Source: French Labour Force Survey from 2003 to 2012.

Table A3 in the appendix presents the characteristics of people living in neighbourhoods composed only of public housing and those of individuals who live in non-public housing neighbourhoods. The population of our public housing sample is more urban than the French average, since 89% of individuals in the sample live in cities of more than 20,000 inhabitants. The proportion of women is also higher than in the private sector, and the average educational level is lower.

[6] In this section, we use the LFS from 2003 to 2012 because we use the sampling identifier as a supplementary control and this identifier is not available in the 2013 and 2014 waves of the LFS.

Table 5 presents the results of the regressions of newcomers' income support participation on the participation rate of the neighbourhood. The first two columns relate to public housing neighbourhoods and show no significant correlation between the proportion of income support recipients in an area and the likelihood of benefitting from that aid. Individuals assignments to public housing seems random regarding income support participation once some observable characteristics are controlled for. The opposite result is found in the last two columns related to the non-public housing neighbourhoods. In this sector, the correlation between the two variables is strong and significant, meaning that people who choose to live close to each other have similar determinants related to the income support participation. Therefore, considering that the assignment to public housing is exogenous, the neighbourhood effect can be evaluated by estimating the relationship between the income support participation of an individual staying in a public housing neighbourhood for more than one year, and the proportion of recipients in that neighbourhood.

Table 5: Endogeneity of assignment in public housing and non-public housing neighbourhoods

	Dependent variable: income support participation			
	Public		Private	
VARIABLES	(Public Housing)		(Non- Public Housing)	
Proportion of recipients in the neighbourhood	0.105	0.054	0.439***	0.428***
	(0.083)	(0.090)	(0.043)	(0.044)
Additional controls	NO	YES	NO	YES
R2	0.15	0.15	0.10	0.10
Total number of observations	4,398	4,398	46,746	46,745

*Notes: *, **, *** represent significance at 1%, 5%, and 10% level, respectively. Standard errors clustered at the neighbourhood level in parentheses. Only individuals who are in the neighbourhood for less than one year are included in the sample. All regressions contain a département fixed effect, the wave of the survey, the type of urban area (urban rural and sensitive urban area) and each individual's age, educational level, activity and socio-professional category. Additional controls in columns 2 and 4 include the average salary, the average educational level and the average age in the neighbourhood*
Source: French Labour Force Survey from 2003 to 2012.

Nevertheless, the social interaction effects are only able to increase the participation of eligible individuals, but most of the individuals are potentially non-eligible for the income support program. Therefore, estimating the neighbourhood peer effects on the participation of each individual would underestimate the true social interaction effects. The main issue is that, we cannot accurately compute each individual's eligibility since the survey was not designed to simulate eligibility (some important information is missing; for instance, we do not know household income and wages for the three months preceding the survey, which is relevant information to simulate the income support eligibility).

To overcome this issue, we use a finite mixture model to divide the population into two components. One part will have a null probability of receiving the benefit and the other part will have a non-null probability of receiving the benefit. Thus, mixing probabilities estimate the corresponding probabilities that an observation is drawn from one of the two populations. In this way, we estimate our coefficients only on the individuals who could benefit from the income support program. The likelihood of our two components model is:

$$f(y) = \sum_{j=1}^{2} \pi_j(z, \alpha_j) p_j(y; x_j' \beta_j, \phi_j)$$

In this model, the parametric distributions p_j are weighted by the mixed probabilities π_j. The component distributions p_j can depend on regressor variables in x_j' and regression parameters β_j. The mixed probabilities π_j, which sum make 1, can depend on regressor variables z and corresponding parameters α_j. We specify a constant distribution with all masses at zero for the ineligible group and a Bernoulli distribution for the eligible group. The results are presented in Table 6.

Table 6: Neighbourhood composition and income support participation

	Without additional controls		With additional controls	
VARIABLES	(1) Probit	(2) Finite mixture model	(3) Probit	(4) Finite mixture model
Average marginal effect	0.111***		0.058***	
	(0.014)		(0.016)	
Average marginal effect on eligible households		0.213***		0.108***
		(0.028)		(0.030)
Individual controls	YES	YES	YES	YES
Neighbourhood Controls	NO	NO	YES	YES
AIC	10,523	10,296	10,481	10,259
Total number of observations	40,769	40,769	40,769	40,769

*Notes: *, **, *** represent significance at 1%, 5%, and 10% level, respectively. Standard errors in parentheses. Only individuals who are in the neighbourhood for more than one year are included in the sample. All regressions contain a departmental fixed effect, the wave of the survey, the type of urban area (urban rural and sensitive urban and the individual's age, educational level, activity and socio-professional category. Additional controls: average salary, average educational level and average age in the neighbourhood as well as employment rate, proportion of men, proportion of individuals living in couple and proportion of EC nationals.*
Source: French Labour Force Survey from 2003 to 2012.

Columns (1) and (3) show the probit results and columns (2) and (4) present the results of the finite mixture model estimation.[7] The overall result is that the likelihood to benefit from the income support is positively correlated with the proportion of recipients in the neighbourhood. Furthermore, using the finite mixture model to account for eligibility, the marginal effect increases. We found that a 1% increase in the proportion of recipients in the neighbourhood raises by nearly 11 percentage points the probability that an eligible household benefits from the aid.[8]

Table 7: Heterogeneity in Neighbourhood Effects by Individual and Neighbourhood Characteristics.

	Dependent variable is: in receipt of one of the allowance					
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
VARIABLES	Female	Male	No child under 18	At least one child under 18	Single	Couple
Net entry of recipients	0.146**	0.040	0.022	0.232***	0.123*	0.239
	(0.069)	(0.062)	(0.037)	(0.083)	(0.096)	(0.381)
Number of observations	10,686	5,593	1,269	11,371	9,125	7,232

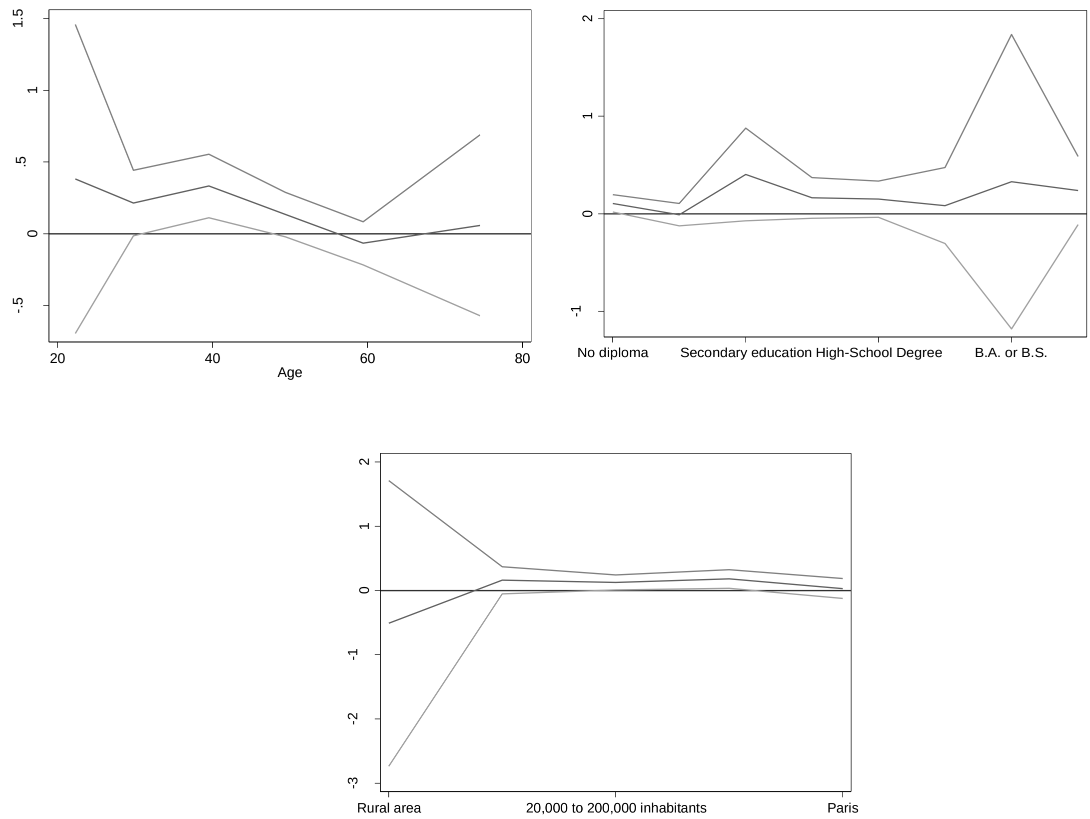
*Notes: *, **, *** represent significance at 1%, 5%, and 10% level, respectively. Standard errors in parentheses. Marginal effects are estimated by running the regressions with interaction terms and computing marginal effects on the subpopulations. By example marginal effect for men is estimated by adding an interaction term between the size of the gender and the participation rate in the regression and then the marginal effect is computed on the subpopulation of men. The number of observations indicated is related to the number of eligible individuals estimated from the posterior probability of the FMM. Controls: the nationality, the matrimonial status, the educational level, the number of children under 18, the size of the urban area, the net wage, the gender, the employment status and the socio-professional category of each individual.*
Source: French Labour Force Survey from 2003 to 2012.

As with the first empirical strategy, we now investigate heterogeneity in neighbourhood peer effects depending on individual and neighbourhood characteristics. Table 7 explores heterogeneity in individuals' responses to neighbourhood changes according to gender (columns (1a)-(1b)), number of children under 18 (columns (2a)-(2b)), and marital status (columns (3a)-(3b)). Again, the results indicate a difference among the subgroups. Nevertheless, compare to the first strategy, the coefficients are only significant for female (at 5%), individuals with at least one child under 18 years old, and singles, increasing by a mean

[7] The probability of being eligible is modelled using as variable for the vector z: the sample number, each individual's age, nationality, marital status, number of children under 18 years old, net pay, gender, employment status, educational level, employment and socio-professional category.
[8] However, it is not possible to exclude that the estimated effect comes partly from neighbourhoods' institutional characteristics like the proximity to a family allowance office (correlated effects). The effect may be somewhat overestimated by a reflection effect: the neighbourhood influences the individual and the individual in return influences the neighbourhood.

of approximately 15, 23, and 12 percentage points, respectively, the probability that “stayer” will receive the income support.

Figure 2: Heterogeneity of the effect depending on the age, the level of educational level, the size of the urban area and the number of inhabitants in the neighbourhood.



Notes: B.A. and B.S. mean Bachelor of Art and Bachelor of Science, respectively. Average marginal effects and confidence intervals at the 90% level are presented. Marginal effects are estimated by running the regressions with interaction terms and computing marginal effects on the subpopulations. For example, the marginal effect in the metropolitan Paris area is estimated by adding an interaction term between the size of the urban area and the participation rate in the regression. Then the marginal effect is computed on the subpopulation of individuals living in the metropolitan Paris area.
Source: French Labour Force Survey from 2003 to 2012.

We investigate heterogeneity depending on the individual’s age and, educational level as well as the size of urban area. The results are presented in Figure 2. Few public housings are constructed in rural areas, consequentially the number of individuals in the sample who are living in rural areas is small and the confidence interval is large. The confidence interval is also large for the youngest and oldest individuals due to the sample size. These large confidence intervals for some points flatten the whole graphs, but despite these distortions, patterns are similar to those derived from the other method. No heterogeneity appears depending on an individual's educational level and the neighbourhood effect is stronger for individuals around 40 years of age and for individuals living in medium-size cities.

Before comparing the results provided by these two strategies, we can note that these estimations are not perfectly comparable. First, for the difference-in-differences strategy, we use a representative sample of the entire French population while for the second strategy we only use a sample of individuals living in public housing. Second, the results from the difference-in-differences strategy are dynamic and capture the effect of a variation in participation within the neighbourhood, while results derived from the second strategy are static and capture the effect of the neighbourhood's proportion of participation.

In addition, the biases accounted by these two strategies differ. The results derived from the public housing assignment strategy do not account for all the potential correlated effects. For instance, we do not control for neighbourhood specificities that may affect the level of knowledge in the area, such as the presence of an administrative building. Another difference comes from the feedback loop that occurs when information or stigma pass through an individual to other individuals in the neighbourhood and then exert a feedback action on the initial individual. This loop, well-known in spatial econometrics (Lesage and Pace, 2009), is not considered here. Consequently, on one hand, the estimate using the public housing assignment may suffer from an upward bias in comparison to the estimation derived from the difference-in-differences strategy.[9] On the other hand, the results from the difference-in-differences strategy did not take into account of the eligibility issue. Applying a finite mixture model (FMM) to this estimation could resolve this issue, but in this dynamic setting we cannot perfectly model eligibility. The main reason is that an individual may be eligible one year but non-eligible another (for instance he could be eligible before the treatment but non-eligible after the treatment). This fact suggests that when using the FMM approach, we must add the hypothesis of constant individual eligibility during the study period to our empirical strategy, which is a strong assumption. Moreover, even if we accept this assumption, with a difference-in-differences strategy, the FMM approach only distinguishes between: i) individuals who have a non-null probability to switch from non-participation in the welfare program to a participation, ii) individuals who have a null probability to switch. The problem is that, among individuals who did not switch, we have two different categories of individuals: those who are non-eligible, and those who participate from the beginning to the

[9] The difference-in-differences estimation may also be affected by the feedback loop, but we can assume that this effect is insignificant due to the limited time period in which this effect could occur.

end of our study period. Then, with this strategy, the FMM is not relevant to account for the eligibility. As a consequence, the results derived from the difference-in-differences strategy are estimated on a sample of individuals including those who are non-eligible; thus, they cannot be affected by the social interaction effects. For this reason, our results underestimate the real neighbourhood peer effects, so they should be interpreted as conservative estimates of the social interaction effects.

Section 7: Conclusion

This paper offers an analysis of the effect of neighbourhood peers on the income support participation of individuals, living in a same neighbourhood. Based on the French LFS dataset, we track approximately 400,000 individuals during a period of 12 years. Each inhabitant of households belonging to these neighbourhood units are interviewed every three months for one and a half years (under the condition that the household stays in the same neighbourhood unit). To analyse these peer effects, we use a reverse engineering approach suggested by Moffitt (2001). Using this approach, we control for a large set of issues. First, this method controls for both unobservable individual characteristics and family-background, neighbourhood fixed effects, cohort and panel wave unobserved shocks as well as *département* trends and trends related to a set of individual characteristics. Second, this approach overcomes the sorting issue in which an individual's characteristics are linked to those of their neighbours through common factors in residential choice. Since some individuals are ineligible and cannot claim welfare benefits, we may underestimate the social interaction effects. We thus use a finite mixture model on a cross section of individuals living in public housing neighbourhoods to account for this issue while dealing with the sorting issue. This strategy distinguishes individuals belonging to an eligible population from those who are ineligible thereby pinning down the bias that could affect our estimates. Since we do not take into account all potential correlated effects, for example those related to the neighbourhood and to the feedback loop, we may overestimate the social interaction effects.

As a consequence, we advocate that these two strategies give us credible lower and upper bounds of the social interaction effects. Additionally, the difference-in-differences strategy estimates social interaction effects on welfare participation while the other strategy based on public housing estimates neighbourhood effects on welfare's take-up. Because the two bounds are positive and significant, our study supports the presence of the social interaction effects in welfare participation. Finally, we investigate potential heterogeneous effects and find a similar pattern between the two strategies. Social interaction effects are stronger for single women, for individuals around 40 years of age, and for those with at least one child under 18 years old. In addition, living in medium-sized cities also increases the social interaction effects.

One of this study's limitation, common in most of the literature, is that we are not able to provide information about the channel through which the social interaction effects appear. Finding a way to distinguish between stigma and information spillover remains on the agenda for future researches. In any case, regarding policy-makers, our results provide empirical support for the existence of a multiplier-effect that should be considered for micro-estimation of the welfare participation response as well as for the design of public policy aimed at reducing the non-take-up.

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Appendix

Table A1: Descriptive statistics

	Mean	Standard deviation
A: Individuals' characteristics, stayers only		
Income support recipient	0.01	0.11
Male	0.47	0.50
Age	48.02	18.97
Nationality (EU 15 country)	0.97	0.17
Lives as a couple	0.53	0.50
Net wage	706.68	1,124.16
Primary schooling	0.13	0.33
Lower secondary (National diploma)	0.12	0.32
Technical (short cycle)	0.24	0.43
Baccalaureate (secondary school leaving qualification)	0.08	0.28
Technical (long cycle)	0.08	0.28
College up to BA	0.01	0.12
BA and plus	0.11	0.31
Employed	0.47	0.50
B: Variation of neighbourhoods' composition		
Net entry of income support recipients	0.00	3.50

Notes: This table presents averages net entry of recipient by number of inhabitants in the neighbourhood in %. The table presents also the mean number of inhabitants as well as the mean number of recipients of the different allowances by neighbourhoods (for stayers only). Number of neighbourhoods: 19 930
Source: French Labour Force Survey from 2003 to 2014.

Table A2: Reasons for Mobility

Percentages reporting following reasons	First reason given by respondent (%)
Change of tenure status	16%
Larger accommodation	14%
More accessible home	10%
Move in with partner	10%
Move out from partner	9%
Job reasons	6%
Moved to better home	6%
Move out from parents	6%
Cheapest accommodation	5%
Dislike area, noise, safety	4%
Move to/from rural area	4%
Other family reasons	3%
Health reasons	2%
Smaller home	2%
Other	4%

Notes: Number of observations: 5,918.
Source: 2012 French Housing Survey.

Table A3: Descriptive statistics on individuals living in Public Housing:

	Non-Public Housing				Public Housing			
	Mean	Standard error	Min	Max	Mean	Standard error	Min	Max
Recipient of income support	0.01	0.12	0.0	1	0.05	0.22	0.0	1
City of less than 20,000 inhabitants	0.18	0.38	0.0	1	0.09	0.29	0.0	1
City of more than 20,000 inhabitants	0.21	0.41	0.0	1	0.30	0.46	0.0	1
City of 200,000 inhabitants or more (apart from Parisian urban area)	0.25	0.43	0.0	1	0.33	0.47	0.0	1
Parisian urban area	0.12	0.33	0.0	1	0.27	0.44	0.0	1
Sensitive urban area	0.04	0.20	0.0	1	0.37	0.48	0.0	1
Education	2.99	2.18	0.0	7	1.98	1.96	0.0	7
Unemployed person	0.05	0.21	0.0	1	0.11	0.31	0.0	1
Student, pupil, trainee	0.09	0.29	0.0	1	0.11	0.31	0.0	1
Other non-working	0.36	0.48	0.0	1	0.35	0.48	0.0	1
Age	47.54	19.60	14.0	105	42.47	18.65	14.0	100
Farmer managers	0.01	0.11	0.0	1	0.00	0.01	0.0	1
Artisans, traders and head managers	0.03	0.18	0.0	1	0.01	0.11	0.0	1
Senior executives and intellectual professions	0.09	0.28	0.0	1	0.02	0.14	0.0	1
Interim professions	0.13	0.33	0.0	1	0.08	0.27	0.0	1
Employee	0.15	0.36	0.0	1	0.21	0.41	0.0	1
Workers	0.12	0.33	0.0	1	0.20	0.40	0.0	1
Retired	0.29	0.45	0.0	1	0.20	0.40	0.0	1
Other individuals without any professional activity	0.17	0.38	0.0	1	0.28	0.45	0.0	1
Married or remarried	0.50	0.50	0.0	1	0.36	0.48	0.0	1
Widow or widower	0.07	0.26	0.0	1	0.07	0.26	0.0	1
Divorced	0.07	0.26	0.0	1	0.12	0.32	0.0	1
Nationality of EC to 15	0.97	0.17	0.0	1	0.88	0.33	0.0	1
Man	0.48	0.50	0.0	1	0.44	0.50	0.0	1
Pay (in thousands of euros)	621.26	1,110.68	0.0	120,000	479.67	735.78	0.0	34,000
Total number of observations	628,101				53,484			

Notes: Educational level is coded from de 0 (unqualified) to 7 (bachelor's degree and more).
Source: French Labour Force Survey from 2003 to 2012.