# EVERYBODY NEEDS GOOD NEIGHBOURS: AT LEAST FOR SOCIAL SUPPORT

**Sylvain Chareyron** [†] **and Patrick Domingues** [‡]

**Preliminary Draft: January 2017**

**Please do not quote or *circulate* without authors' permission**

**Abstract:**

*We estimate the effect of neighborhood peer effects on individual welfare participation in France using a reverse engineering approach. We exploit variation that arise purely through residential migration in the number of individuals participating to a social program in a neighborhood on the take-up rate of individuals that stay in this same geographical area during this period. Furthermore we investigate heterogeneity and non-linearity in the effect of neighborhood participation regarding the kind of welfare program as well as individual and neighborhood characteristics. Our results show that the rate of welfare participation in the neighborhood has a significant effect on individual welfare participation. We also show that this effect is particularly strong in small cities and rural areas as well as in neighborhoods with an initially level of participation below the median take-up rate of our sample.*

**Keywords:** neighborhood effects, social interaction, welfare participation

**JEL Code:** H55; I38; D62

[†] University Paris-Est (UPE), ERUDITE and TEPP (FR CNRS 3435) : sylvain.chareyron@univ-paris-est.fr, 61 Av. du Général de Gaulle 94010 Créteil, 0699432282.

[‡] University Paris Est Créteil (UPEC), ERUDITE: patrick.domingues@u-pec.fr, 61 Av. du Général de Gaulle 94010 Créteil,

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 persons eligible for social assistance either do not claim it or, in any case, do not receive it. This results has been highlighted by many studies in different contexts (Currie 2006) and among all the explanation, two main mechanisms emerged from the literature. The first is that eligible people suffer from a lack of information linked to information cost about how to take-up the social support (McGarry, 1996 Tempelman et al 2015). The second is related to a stigma associated with the claim (R. Moffitt 1983). Following these explanations the neighborhood composition may affect the information availability and the level of stigma suffered by an individual, thus resulting in a substantial impact on the take-up rate.

The effect of social networks and information spillovers from the neighborhood are highlighted to have an important effect on different aspect of individual behaviors such as educational attainments (Goux and Maurin 2007), teenage childbearing (Crane 1991), criminal activities (Glaeser, Sacerdote, and Scheinkman 1996) or human capital acquisition (Borjas 1995). Based on these evidences, this paper investigates how social interactions affects the take-up of social benefit, using data from the French Labour Force Survey (FLS) (from 2003 to 2014).

In order to define social interaction, we follow the typology of Manski (2000) that describe apparent social interaction as the result of three different phenomenon: contextual interactions (when the behavior of an individual vary with exogenous characteristics of the group), endogenous interactions (when the behavior of an individual is influenced by the behavior of the group) or correlated effects (when the behavior of an individual is similar to those of their neighbors because they have a similar institutional environment). Following this canonical paper, only the two first phenomenon characterize the influence of the social environment while the correlated effects are not a social phenomenon. Therefore the main challenge is to separate the causal effect of social interaction from the correlated effect.

Regarding the literature about the effect of social interactions on welfare participation previous studies show a substantial effect among ethnic minorities (Aizer and Currie 2004; Bertrand, Luttmer, and Mullainathan 2000). More recently, Anne and Chareyron (2017) also suggest potential information spillovers between households regarding their participation to a program that allow free public transportation. However the existing literature also provides evidence that neighborhood and social network do not affect the welfare participation. For instance, using a randomized control trials (Bettinger et al. 2012; Katz, Kling, and Liebman 2001) find no significant effect of the quality of the neighborhood in welfare participation. Nevertheless, the major shortcoming of these studies is that they do not distinguish between social interactions and correlated effects. In order to separate social interactions from the correlated effects some few studies have used an IV strategy. For instance, Rege, Telle, and Votruba (2012) used plant-downsizing events as an instrument variable for the disability pension program entry rate among the individual's previously employed neighbors. Shang (2013) uses the variation in welfare benefits and neighborhood demographic composition to address the reflection problem and the omitted neighborhood variables problem.

Toward the same aims Gibbons, Silva, and Weinhardt (2013) offer an alternative strategy to disentangle social interactions and correlated effects in order to investigate how neighborhood affects educational attainment of children and to account both for the sorting issue, the reflection problem and the omitted variables issue at the individual and neighborhood level. This strategy relies in a difference-in-differences estimation, where the treatment is a change in the characteristics of neighborhood peers. This research design captures directly the impact of residential movers on individuals who do not move in order to identify the causal effects of neighborhood composition. These authors found no significant effect of changes in the neighborhood on teenage educational attainment. However, unlike investigations on education performance, a particular problem arise for the analyses of neighborhood effects on welfare participation: some individuals may not be eligible for social programs. In this case the social interaction effect is may be downward biased because it can affect only a limited proportion of the population.

Therefore, this paper contributes to the existing literature about the effect of social interactions on welfare participation, offering to use the approach of Gibbons, Silva, and Weinhardt (2013) to identify neighborhood effects. More precisely, we regress the variation in number of individuals participating to a social program in a neighborhood, during one year and half, on the take-up rate of individuals that stay in this same geographical area during this period. Furthermore, the second contribution of this paper is to advance this strategy in order to deal with the eligibility issue specific to the outcome analyzed here, in combining this approach with a finite mixture model estimation. We believe that this research design represents the most suitable way to distinguishing social interactions and correlated effects in order to investigate how neighborhood effects impact the participation to welfare programs. Our main result is that we identify a significant positive neighborhood effect in the participation to welfare programs even if of relatively low magnitude: our estimated social multiplier is 1.07. This effect is relevant for the majority of French welfare programs except for the Disabled Adults' Allowance (DAA). We also point out that this effect is stronger in small cities and rural areas: in these areas the social multiplier goes up to 1.15. Finally, the neighborhood effects appear to be relevant only in neighborhoods with an initial level of participation below the median.

The next section discusses data that we use and the French social context. Section 3 describes the empirical strategy and section 4 presents descriptive statistics, results and robustness checks. Section 5 details the results for different subpopulation and section 6 concludes.

# Section 2 Data and social context

## Data

To investigate the effect of the social interactions in the individual participation to social benefits, we used data from 12 waves of the Labour Force Survey (LFS) conducted in France, each year by the Institut national de la statistique et des études économiques (INSEE) (from 2003 to 2014). This survey is designed to collect both annual and quarterly information on individuals over 15 years of age living within various groups of approximatively 20 adjacent households, who are defined as a neighbourhood unit. More specifically this survey includes data for 26,064 neighbourhoods and each inhabitant of households belonging to these units are interviewed each 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 of time). Data recorded in this survey are multipurpose. Hence, this survey collects information on gender, date and place of birth, nationality, family composition, labour market situation and the education level. This survey also provides data about the participation to social programs of each respondent. However this topic is only investigated during the first and the last of the six interviews. Furthermore, using this survey we can identify the net entry of individuals (and households) in a particular neighbourhood unit during the interview period. 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 of the six interviews (defined as, the stayers), the data contains 411,705 individuals living in 19,924 different neighbourhoods. Therefore, combining these two last information, we can evaluate the effect of this variation on the participation to social programs of individuals who stay in the same unit over this period.

## Social context

The French welfare system display a quit important diversity of mean-tested welfare programs. For this study we are interested, on the effects of social interactions on five specific welfare programs. First, the income support program that is designed to sustain low income households and to facilitate their professional and social insertion. Second, the Disabled Adults' Allowance (DAA) that is a mean-tested allowance paid to adults who are declared disabled, in order to guarantee them a minimum income. Third, the Solidarity Allowance for Elderly People (SAEP) is an allowance intended specifically to elderly people who have low income, in order to guarantee them a minimum level of income.[1] Fourth, the Early Childhood Benefit (ECB) is a family allowance that can be perceive at the birth of the child. Fifth, the unemployment insurance to employees who can prove a minimum duration of work prior to the unintentional loss of their job. Furthermore, we also create a dummy variable that takes 1 if the person receive at least one of these program and 0 otherwise.

All of these welfare programs have to be claimed by eligible individuals. As a consequence some eligible people do not claim or do not receive it. This phenomenon is defined as a non-take-up of social benefit. Some people may not receive the program while eligible.2 As a consequence the receipt of these programs may depend on the level of information and stigma owned by the individuals (R. Moffitt 1983). As the level of information and stigma of a person may be influenced by his neighbours we expect that the participation to these welfare programs is potentially affected by social interactions.

## Section 3 Hypothesis and Empirical strategy

As pointed out in the introduction, the identification of a proper effect of social interaction is difficult. To differentiate social interactions from correlated effect we will used a reverse engineering approach proposed by R. A. Moffitt (2001) and applied by Gibbons, Silva, and Weinhardt (2013) on educational outcome. This method consists to study changes in the outcome of the original residents receiving new households in the neighborhoods. For them, neighborhood remains the same except that their composition is affected by the newcomers. In this way the estimated coefficient will not be affected by characteristics specific to the neighborhood.

In our case we exploit changes in neighborhood compositions induced by migration to estimate the effects of these changes on the participation to the welfare program of the stayers. This approach permits to control for neighborhood specificities, such as factors affecting local perception and information about welfare programs (information campaigns, distance to the administration…) and to identify separately the effects arising from changes in neighborhood composition, which Gibbons, Silva, and Weinhardt (2013) call “neighborhood peer effects”.[3]

To estimate the model we use a change-in-change design. The reduced-form of the linear relation between the decision to participate to a welfare program of an individual and the characteristics of peers in the neighborhood, other neighborhood infrastructure and individual characteristics is:

$$y_{inct} = z_{nct}\beta + x_i'y + x_i'\delta_t + \varepsilon_{inpct}$$

[1] It replaced the minimum old-age pension in 2006.

[2] A number of studies have shown the prevalence of the phenomenon on the income support (S. Chareyron 2014; Sylvain Chareyron and Domingues 2015; P. Domingo and Pucci 2014; Pauline Domingo and Pucci 2011) and on the unemployment allowance (Blasco and Fontaine 2010).

[3] Note that the estimated coefficient does not represent what Manski (2000) call endogenous interactions because the effects of neighbors’ behavior are not separately identified from the effects of the neighbors‘ characteristics that give rise to those behaviors.

Where $y_{inct}$ denotes the outcome of individual *i* living in neighborhood *n*, belonging to birth cohort *c* and measured at age *t*. The outcomes will be the perception of one of the welfare program previously mention and we will conduct, alternatively, estimations on each welfare program participation. $z_{nct}$ is measuring neighbor mean prior composition and $x_i'$ contains individual observable characteristics with a potential time-trending effect captured by $\delta_t$. The error term is assumed to be:

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

Where $\alpha_i$ represents an unobserved individual-level fixed effect that captures all constant personal and family background characteristics. $\phi_n$ represents unobserved neighborhood characteristics. $\vartheta_{ct}$ is a cohort specific shock and $\tau_{pt}$ is a panel wave specific shock which may capture variation in welfare perception or information that is common to individuals belonging to the same cohort on a same panel wave. $e_{inct}$ is assumed to be uncorrelated with the right hand side variables but endogeneity issues arise because the components $\alpha_i$, $\phi_n$, $\vartheta_{ct}$ and $\tau_{pt}$ are potentially correlated with $z_{nct}$ and $x_i'$.

To eliminate the unobserved components that could jointly determine neighbor-peer composition and individuals participation in welfare program, we take within-individual differences between the first and the last interview:

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

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

$$(e_{inc1} - e_{inc0}) = (\vartheta_{c1} - \vartheta_{c0}) + (\tau_{p1} - \tau_{p0}) + \upsilon_{inpct}$$

The differencing eliminates the individual and the neighborhood unobserved components that are fixed over time. $\upsilon_{inct}$ 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 different perception variations during the life cycle and the year concerned. We thus include a cohort-by-panel-wave fixed effect to absorb this source of variation.

Most of the individuals are eligible to none of the social programs studied here. The arrival of participants in the neighborhood is only able to increase the receipt's probability of eligible. Estimating the effect of changes in neighborhood participation on the participation of each stayer would thus underestimate the true social interaction effect. We do not own the information necessary to accurately compute the eligibility of each individuals thus we use a finite mixture model to separate the population into two components. One part of the population will have a null probability to receipt benefit and the other part of the population will be able to receive the benefit. The 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 individual who are able to benefit from the program studied. 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 mixing probabilities $\pi_j$. The component distributions $p_j$ can depend on regressor variables in $x_j$ and regression parameters $\beta_j$. The mixing probabilities $\pi_j$, which sum to 1, can depend on regressor variables z and corresponding parameters $\alpha_j$. We specify a constant distribution with all mass at zero for the ineligible group and a Bernoulli distribution for the eligible group.

## Section 4: Results

### Summary Statistics

Table 1 summarizes the main variables for individuals who do not move (defined as stayers). Around 9% of stayers receive one of the allowance analyzed in this paper. In particular, regarding the three main French social programs, 3% of these individuals are in receipt of the unemployment allowance, 2% receive the ECB and 1% receive the income support. Table 2 presents the means and standard deviations of the neighborhood-peer characteristics and their changes during the year and half of the observation. Neighborhoods have on average around 35 inhabitants with a mean of around 2 individuals in receipt of a welfare program and less than one individual in receipt of income support or unemployment allowance. The neighborhood unit is thus composed from a small population of individuals, this means that we are focusing on small groups of individuals close to each other.

Table 1: Individuals' characteristics, stayers only

| | Mean | Standard deviation |
|---|---|---|
| ECB recipient | 0.02 | 0.13 |
| DAA recipient | 0.01 | 0.12 |
| Income support recipient | 0.01 | 0.11 |
| SAEP recipient | 0.01 | 0.09 |
| Unemployment allowance recipient | 0.03 | 0.18 |
| In receipt of one of the allowance | 0.09 | 0.29 |
| Male | 0.47 | 0.50 |
| Age | 48.02 | 18.97 |
| Nationality of one of the 15 UE country | 0.97 | 0.17 |
| Lives as a couple | 0.53 | 0.50 |
| Net wage | 706.68 | 1124.16 |

| | | |
|---|---|---|
| Primary schooling | 0.13 | 0.33 |
| Lower secondary (National diploma) | 0.12 | 0.32 |
| Technical (short cycle) | 0.24 | 0.43 |
| Baccalaureat (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 |

*Table 2 : Variation of neighborhoods' composition*

| | Mean | Standard deviation |
|---|---|---|
| Net entry of ECB recipients | -0.02 | 2.61 |
| Net entry of income support recipients | 0.00 | 3.50 |
| Net entry of DAA recipients | -0.04 | 2.28 |
| Net entry of SAEP recipients | -0.02 | 1.78 |
| Net entry of unemployment allowance recipients | -0.05 | 5.63 |
| Net entry of recipients in the neighborhood | -0.13 | 9.05 |
| Mean number of inhabitants | 35.08 | 11.95 |
| Mean number of ECB recipients | 0.34 | 0.72 |
| Mean number of initial income support recipients | 0.28 | 0.74 |
| Mean number of initial DAA recipients | 0.28 | 0.63 |
| Mean number of initial SAEP recipients | 0.19 | 0.60 |
| Mean number of initial unemployment allowance recipients | 0.71 | 0.99 |
| Mean number of initial recipients of one of the allowance | 1.86 | 2.02 |

*Notes: This table presents averages net entry of recipient by number of inhabitants in the neighborhood in %. The table presents also the mean number of inhabitants as well as the mean number of recipients of the different allowances by neighborhoods (for stayers only). Number of neighborhoods : 19 930.*

## Results

Table 3 presents the finite mixture model results on the relationship between variations of the neighborhood composition and receipt of one of the allowance for stayers, whatever the social welfare program considered.[4]. Column (1) presents results from a regression that does not includes any control variables, and column (2) reproduces this estimation including cohort dummies and panel fixed effect. As a preliminary result, we find that the arrival of one new recipient, by initial number of inhabitants in the neighborhood, increases the probability that eligible individuals receipt at least one of the allocation considered in this study. This result is statistically significant at 1% level. However, the introduction of cohort and panel fixed effects divide by near to three the magnitude of the estimated coefficient. Then, columns (3) and (4) reproduce the strategy presented in columns (1) and (2) but including control variables capturing individual's characteristics. We add the nationality, the matrimonial status, the age, the net wage, and the gender of each individual. Comparing with previous estimations without individual controls, our results are not substantially affected. We still find a

[4] We specify a Bernoulli distribution of the dependent variable with a normal link.

positive and significant effect of social network on welfare participation. Regarding this point, as noted by (Gibbons, Silva, and Weinhardt 2013), the similarity of the results in Column (1)-(3) and (2)-(4) comforts our main finding, since this implies that changes in neighborhood-peers composition are not strongly linked to individuals' background characteristics. Furthermore, this support the identification strategy that, which relies on changes in the treatment variables to be "as good as random" once we partial out individual and neighborhood-fixed effects. Finally, to go further in this analysis, following the AIC criteria our preferred specification is those presented in column (6). These results indicates that the arrival of one new recipient (that is a net entry by initial number of inhabitants in the neighborhood) increases in mean by 6.4 percentage points the probability that eligible individuals receipt one allocation (whatever the social welfare program considered). Our social interaction effect β can give rise to a social multiplier φ that strengthens the effect of policy changes and economic shocks on aggregate participation rate (Rege, Telle, and Votruba 2012). As mentioned by Glaeser, Scheinkman, and Sacerdote (2003) this social multiplier can be computed as 1/(1- β). Our estimate implies a social multiplier of 1.07 using the FMM estimation.

Table 3: Neighborhood composition and general benefit participation (finite mixture model)

| | No control | | With controls | |
|---|---|---|---|---|
| VARIABLES | (1)<br>In receipt of one of the allowance | (2)<br>In receipt of one of the allowance | (3)<br>In receipt of one of the allowance | (4)<br>In receipt of one of the allowance |
| Net entry of recipients of one of the allowance | 1.541*** | 0.619*** | 1.637*** | 0.520*** |
| | (0.089) | (0.151) | (0.085) | (0.186) |
| Mean marginal effect of the eligible individual | [0.367] | [0.110] | [0.221] | [0.064] |
| Mean marginal effect of the sample | [0.368] | [0.166] | [0.277] | [0.093] |
| Controls | NO | NO | YES | YES |
| Cohort fixed effect | NO | YES | NO | YES |
| Panel fixed effect | NO | YES | NO | YES |
| AIC | 397 111 | 338 717 | 360 634 | 331 733 |

Notes: *** p<0.01, ** p<0.05, * p<0. Number of observations approximately 400 000 in approximately 20 000 neighborhoods. Controls: nationality, the matrimonial status, the age, the net wage, and the gender of each individual.

Table 4 presents the effect of neighborhood composition on the different programs: the income support (Column (1)), the DAA (Column (2)), the ECB (Column (3)), the unemployment insurance (Column (4)), the SEAP (Column (5)). The effect of social network is significant on income support, ECB, unemployment insurance and SAEP with a particularly large effect for ECB and SAEP programs. It appears that the neighborhood composition has no significant effect on the probability to receive DAA. One potential explanation is that disabled adults are better informed because they are in contact with the administration and they beneficiate from a long term social assistance thus they are more likely to take-up this specific social support. As a consequences, the non-take up linked to stigmata or a lack of information is unlikely to be relevant explanation for them.

Table 4: Neighborhood composition and participation to the different allowance (finite mixture model)

| VARIABLES | (1)<br>In receipt of income support | (2)<br>In receipt of the DAA | (3)<br>In receipt of the ECB | (4)<br>In receipt of the unemployment insurance | (5)<br>In receipt of the SAEP |
|---|---|---|---|---|---|
| Net entry of recipients of one of the allowance | 1.023** | 0.015 | 3.201*** | 0.638*** | 4.128*** |
| | (0.406) | (0.763) | (0.498) | (0.224) | (0.632) |
| Mean marginal effect of the eligible individuals | [0.061] | [0.001] | [0.092] | [0.035] | [0.087] |
| Mean marginal effect of the sample | [0.107] | [0.002] | [0.255] | [0.059] | [0.111] |
| Controls | YES | YES | YES | YES | YES |
| Cohort fixed effect | YES | YES | YES | YES | YES |
| Panel fixed effect | YES | YES | YES | YES | YES |

Notes: *** p<0.01, ** p<0.05, * p<0.1

## Section 5: Extension

In this section we investigate heterogeneity and non-linearity in neighborhood peer-effects depending on the characteristics of individuals and neighborhoods. Table 5, columns (1a)-(1b) to (3a)-(3b) exploring heterogeneity in individuals' response to neighborhood changes according to whether the individual is male or female, educated or not and living as single or as a couple. Columns (4a)-(4b) to (6a)-(6b) present heterogeneity according to whether the neighborhood is rural or urban, above or below the median number of inhabitants and above or below the median propensity of benefit recipients. It appears first that neighborhood effects do not vary much depending on individual characteristics: living as a couple or as a single does not lead to significantly different effects as well as having higher education compared to secondary education or lower. There is however much more difference regarding neighborhood characteristics. First, the effect seems to affect mainly individuals living in neighborhoods belonging to small cities or rural area, but not those living in cities of more than 20,000 inhabitants. The effect is particularly high for rural and small city neighborhoods with a social multiplier of about 1.15. Second the neighborhood effects appear to be relevant only in neighborhoods with an initial level of participation below the median. This seems to indicate that the value of the new entrants is higher when the initial level of participation is low.

Table 5: Heterogeneity in Neighbourhood Effects by Individual and Neighbourhood Characteristics

| | Dependent variable is: in receipt of one of the allowance | | | | | |
|---|---|---|---|---|---|---|
| VARIABLES | (1a)<br>Female | (1b)<br>Male | (2a)<br>Secondary education or lower | (2b)<br>Superior education | (3a)<br>Single | (3b)<br>Couple |

| | | | | | | |
|---|---|---|---|---|---|---|
| Net entry of recipients of one of the allowance | 0.468 | 0.486** | 0.499** | 0.496* | 0.486*** | 0.494* |
| | (0.292) | (0.239) | (0.209) | (0.291) | (0.214) | (0.254) |
| Mean marginal effect for the eligible individual | [0.047] | [0.059] | [0.057] | [0.051] | [0.053] | [0.124] |
| Mean marginal effect for the sample | [0.054] | [0.096] | [0.085] | [0.070] | [0.080] | [0.127] |
| Observations | 422 777 | 371 757 | 640 080 | 92 896 | 367 609 | 426 925 |

| | Dependent variable is: in receipt of one of the allowance | | | | | |
|---|---|---|---|---|---|---|
| | (4a) City of less than 20,000 inhabitants | (4b) City of more than 20,000 inhabitants | (5a) Small neighbourhood | (5b) Large neighbourhood | (6a) Neighbourhood with low propensity of recipients | (6b) Neighbourhood with high propensity of recipients |
| Net entry of recipients of one of the allowance | 1.216*** | 0.228 | 0.400* | 0.987** | 0.880*** | 0.117 |
| | (0.465) | (0.242) | (0.210) | (0.429) | (0.191) | (0.135) |
| Mean marginal effect for the eligible individual | [0.131] | [0.026] | [0.053] | [0.114] | [0.060] | [0.025] |
| Mean marginal effect for the sample | [0.176] | [0.033] | [0.072] | [0.178] | [0.093] | [0.030] |
| Observations | 284 954 | 419 073 | 397 981 | 396 553 | 393 223 | 401 311 |

Notes: *** p<0.01, ** p<0.05, * p<0. Controls: nationality, the matrimonial status, the age, the net wage, and the gender of each individual.

## Section 6: Conclusion

This paper offers an analysis of the effect of neighborhood peers on the welfare participation of individuals, living in a same neighborhood. Base on the French LFS dataset, we track about 400,000 individuals during a period of 12 years. Each inhabitant of households belonging to these neighbourhood units are interviewed each three months during a period of one year and half (under the condition that the household stays in the same neighbourhood unit). In order to analyse these peer effects, we use a reverse engineering approach suggested by R. A. Moffitt (2001) combining a difference-in-difference strategy proposed by Gibbons, Silva, and Weinhardt (2013) and a finite mixture model. 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 as well as cohort and panel wave unobserved shocks. Second this approach overcomes the sorting issue which is that individual's characteristics are linked to those of their neighbours through common factors in residential choice. Third, since some individuals are ineligible and they cannot claim a welfare program, we use of a finite mixture model. This strategy distinguish individuals belonging to an eligible population from those ineligible and thus pinning down the bias that could affect our estimates. Therefore we estimate a credible unbiased estimate of neighbourhood peer effects. Fourth, we investigate a potential heterogeneous effect and non-linearity on both different welfare programs and subpopulation.

Following this approach, we identify a significant neighbourhood peer effects on the participation to welfare program. The estimated effect is however not large. We find a social multiplier of about 1.07. This effect appears thus to be lower than those estimated by instrumental variable methods (Rege, Telle, and Votruba 2012; Shang 2013). Extending our analyses to different programs and subpopulation we find that the effect is significant for many French welfare programs. Furthermore, this effect appears to be particularly strong in small cities and rural areas cities (where people are more connected to their neighbours). Moreover we find that for neighbourhood effects appear to be relevant only in neighborhoods displaying an initially level of participation below the median. For policy-makers, our results give empirical support to the existence of a multiplier-effect that should be considered for micro-estimation of the welfare participation response.

## References:

Aizer, Anna, and Janet Currie. 2004. "Networks or Neighborhoods? Correlations in the Use of Publicly-Funded Maternity Care in California." *Journal of Public Economics* 88 (12): 2573–85. doi:10.1016/j.jpubeco.2003.09.003.

Anne, Denis, and Sylvain Chareyron. 2017. "Une Analyse Spatiale Du Non-Recours Aux Dispositifs Sociaux." *Revue D'économie Politique*.

Bertrand, Marianne, Erzo F. P. Luttmer, and Sendhil Mullainathan. 2000. "Network Effects and Welfare Cultures." *The Quarterly Journal of Economics* 115 (3): 1019–55. doi:10.1162/003355300554971.

Bettinger, E. P., B. T. Long, P. Oreopoulos, and L. Sanbonmatsu. 2012. "The Role of Application Assistance and Information in College Decisions: Results from the H&R Block Fafsa Experiment." *The Quarterly Journal of Economics* 127 (3): 1205–42. doi:10.1093/qje/qjs017.

Blasco, Sylvie, and François Fontaine. 2010. "Étudier le non-recours à l'assurance chômage." *Revue économique* Vol. 61 (5): 933–43.

Borjas, George J. 1995. "Ethnicity, Neighborhoods, and Human-Capital Externalities." *The American Economic Review* 85 (3): 365–90.

Chareyron, S. 2014. “Le Non-Recours Au RSA ‘socle Seul’ : L’hypothèse Du Patrimoine.” TEPP Research Report. TEPP,.
Chareyron, Sylvain, and Patrick Domingues. 2015. “Take-up of Social Assistance Benefits: The Case of Homeless.” TEPP Working Papers. TEPP.
Crane, Jonathan. 1991. “The Epidemic Theory of Ghettos and Neighborhood Effects on Dropping Out and Teenage Childbearing.” *American Journal of Sociology* 96 (5): 1226–59. doi:10.1086/229654.
Currie, Janet. 2006. “The Take-up of Social Benefits.” In *Public Policy and the Income Distribution*, New York: Russell Sage Foundation, 80–148. Alan J. Auerbach, David Card, and John M. Quigley.
Domingo, P., and M. Pucci. 2014. “Impact Du Non-Recours Sur L’efficacité Du RSA Activité Seul.” *Economie et Statistique*, 117–140,.
Domingo, Pauline, and Muriel Pucci. 2011. “Le Non-Recours Au Revenu de Solidarité Active.” Annexe 1 du rapport du Comité national d’évaluation du RSA.
Frick, J. R., and O. Groh-Samberg. 2007. “To Claim or Not to Claim: Estimating Non-Take-up of Social Assistance in Germany and the Role of Measurement Error.” Discussion Papers of DIW Berlin. DIW Berlin, German Institute for Economic Research,.
Gibbons, Stephen, Olmo Silva, and Felix Weinhardt. 2013. “Everybody Needs Good Neighbours? Evidence from Students’ Outcomes in England.” *The Economic Journal* 123 (571): 831–74. doi:10.1111/ecoj.12025.
Glaeser, Edward L., Bruce Sacerdote, and Jose A. Scheinkman. 1996. “Crime and Social Interactions.” *The Quarterly Journal of Economics* 111 (2): 507–48.
Glaeser, Edward L., Jose A. Scheinkman, and Bruce I. Sacerdote. 2003. “The Social Multiplier.” *Journal of the European Economic Association* 1 (2/3): 345–53.
Goux, Dominique, and Eric Maurin. 2007. “Close Neighbours Matter: Neighbourhood Effects on Early Performance at School*.” *The Economic Journal* 117 (523): 1193–1215. doi:10.1111/j.1468-0297.2007.02079.x.
Katz, L. F., J. R. Kling, and J. B. Liebman. 2001. “Moving to Opportunity in Boston: Early Results of a Randomized Mobility Experiment.” *The Quarterly Journal of Economics* 116 (2): 607–54. doi:10.1162/00335530151144113.
Manski, Charles F. 2000. “Economic Analysis of Social Interactions.” *Journal of Economic Perspectives* 14 (3): 115–36. doi:10.1257/jep.14.3.115.
Moffitt, Robert. 1983. “An Economic Model of Welfare Stigma.” *American Economic Review* 73 (5): 1023–35.
Moffitt, Robert A. 2001. “Policy Interventions, Low-Level Equilibria And Social Interactions.” In *Social Dynamics*, Durlauf SN, Young HP, 45–82. MIT Press.
Rege, Mari, Kjetil Telle, and Mark Votruba. 2012. “Social Interaction Effects in Disability Pension Participation: Evidence from Plant Downsizing*.” *The Scandinavian Journal of Economics* 114 (4): 1208–39. doi:10.1111/j.1467-9442.2012.01719.x.
Shang, Qingyan. 2013. “Endogenous Neighborhood Effects on Welfare Participation.” *Empirical Economics* 47 (2): 639–67. doi:10.1007/s00181-013-0754-x.

# Appendix

Table A1: Neighborhood composition and general benefit participation

| VARIABLES | (1)<br>In receipt of one of the allowance | No control<br>(2)<br>In receipt of one of the allowance | (3)<br>In receipt of one of the allowance | (4)<br>In receipt of one of the allowance | With controls<br>(5)<br>In receipt of one of the allowance | (6)<br>In receipt of one of the allowance |
|---|---|---|---|---|---|---|
| Net entry of recipients of one of the allowance | 1.125*** | 0.509*** | 0.504*** | 0.130*** | 0.412*** | 0.416*** |
| | (0.071) | (0.075) | (0.075) | (0.077) | (0.084) | (0.084) |
| | [0.173] | [0.073] | [0.072] | [0.178] | [0.073] | [0.073] |
| Controls | NO | NO | NO | YES | YES | YES |
| Cohort fixed effect | NO | YES | YES | NO | YES | YES |
| Panel fixed effect | NO | YES | YES | NO | YES | YES |
| Cohort*Panel fixed effect | NO | NO | YES | NO | NO | YES |