Neighborhood effect and Labor Market Integration*

Matthieu Solignac† Maxime Tô‡

January 20, 2013

Abstract

The 2008 economic crisis has resulted in a dramatic increase of youth unemployment in most developed countries. A 26.5 per cent increase in their number and a rate remaining close to the crisis peak is still recorded in 2012. These striking levels are not yet a new feature for some labour market like in France and recent studies reveal major disparities according to the residential location, even at a very local level. One hypothesis is that youth may be influenced by the behavior of their neighborhood peers in getting a job. The identification of this endogenous social effect from the sorting process requires implementing specific identification strategies. Two complementary approaches are developed in this paper using representative samples of youth leaving the French educational system (*Génération 1998* and *Génération 2004* panel surveys from the Céreq). We first implement an instrumental variable approach using employment conditions in different nearby areas as instruments of the neighborhood employment level. Then, we assume a random assignment within the neighborhood, taking the very local variation of employment level as exogenous. In both estimation strategies, the positive impact of local employment conditions on job access remains significant suggesting that the employment situation of local peers matters to successfully enter the job market.

Keywords: Neighborhood effect, Peer effects, Youth unemployment

*This work is conducted with the support of the French Center for Research on Education and Employment (Céreq) and the General Secretary of the French Interministerial Committee for Cities (SG-CIV). They coordinate a working group ("Débuts de carrière et inscription spatiale infra-urbaine") to exploit newly introduced geolocation data in the Céreq *Génération* surveys.

†Aix-Marseille University (Aix-Marseille School of Economics), CNRS and EHESS, Université Paris 1 Panthéon-Sorbonne University, INED. E-mail : matthieu.solignac@univ-amu.fr

‡CREST, Sciences Po. Address : 15 Boulevard Gabriel Peri 92245 Malakoff Cedex, France. E-mail : maxime.to@ensae.fr

Introduction

The explosion of youth unemployment stands among the main lasting consequences of the 2008 financial crisis. Over four years, young people have been the hardest hit by the job crisis and youth unemployment remains at crisis peak levels. The International Labor Organization reports a 26.5 per cent increase in the number of unemployed youths and warns that this situation will not improve in the coming years, especially in Europe (International Labor Organization (2012)). Striking high levels of youth unemployment relative to older groups are not uncommon in some countries. Over the last decades, high average levels of youth unemployment have even become a feature of some labour market, such as in France. For 40 years, the unemployment rate of men between 15 and 24 years old have been at least twice above the average rate, and remains a constant concern for public agencies. Their lower level of education, their loss of work experience or their foreign origin only partly explain a gap which varies widely across the country, even at a very local level. The 2005 civil unrest highlighted the difficulties faced by youth from french deprived suburbs on the labor market. It is widely accepted that living in housing projects has an impact on getting a job. Moreover leaving parents' home has became harder as youths face relative scarcity and high price of accommodation facilities, especially in the main urban areas. Numerous youth remains stuck in their parent's neighborhood whereas current dynamic areas in terms of employment might be far away. However, the mechanisms explaining how spatial location can affect individual success are much debated.

Many recent studies in economics investigate the role social interactions have in explaining these differences observed from one neighborhood to another[1]. Following the early work of Manski (1993), social effects can be explained by at least three channels. First, individuals act similarly because they face similar contexts and situations (exogenous contextual effect). Second, individuals from the same neighborhood act similarly because they have similar characteristics (sorting effect). And finally, the endogenous social effect implies that the behavior of one individual is directly influenced by the behavior of others living in his neighborhood. In the case of employment, the three channels may be relevant. For example, getting a job does not only depend on the characteristics of an individual (e.g. level of education, family background), but also on his neighbors' characteristics. Their socio-economic characteristics are a main factor of the neighborhood reputation. Discrimination based on the candidates' place of residence may partly be explained by statistical discrimination from employers, its neighbors characteristics being attributed to the candidate. Such a redlining effect is one of the effects gathered under the name of the spatial mismatch hypothesis, explaining the disconnect between residential location of labor demand and job offers (Gobillon, Selod, and Zenou (2007)). But other mechanisms underlying spatial mismatch depend on the employment situation of neighbors. An information mechanism states that employed workers are more aware of job opportunities and inform their neighbors (Calvo-Armengol and Jackson (2004)). Through a stigma channel, deviant behavior is socially more costly to support and individuals living in areas

[1] See Blume, Brock, Durlauf, and Ioannides (2011) and Ioannides and Topa (2010) for extended surveys on recent works about social interactions and neighborhood effects.

where employment is high make more important efforts to find jobs (Stutzer and Lalive (2004)).

As suggested by Manski (1993), the identification of the different channels is a difficult task. However, in the case of employment, the binary form of the output of the model allows to identify the existence of social effects. Brock and Durlauf (2001, 2007) show that binary choice model with social interactions can be identified. Self-selection into neighborhoods remains a major concern for the identification of social effects. To address this problem, one has to make assumptions on the individual's neighborhood choice. To correct this source of endogeneity, one can directly model the neighborhood choice (Nesheim (2004), Bayer, Ferreira, and McMillan (2007)) but such a work is demanding computationally and in the necessary data. A first alternative approach is the method of instrumental variables, taking employment conditions in different nearby areas as instruments of the neighborhood employment level. Used by Evans, Oates, and Schwab (1992) to explore the link between teenage behaviors and school composition, this framework can be adapted to the case of employment if we assume that an individual is directly affected by the employment rate in his neighborhood, but that rates in other neighborhoods do not directly affect his employment outcome. Another alternative approach following Bayer, Ross, and Topa (2008) is to focus on a very small area, making the assumption that individuals may choose a neighborhood, but that inside of it, the block level composition is random. Fixed effects taking into account the characteristics of the neighborhood, the remaining spatial variance of employment rates are supposed to be exogenous.

This paper contributes to the existing research by using two methods of estimation based on local employment variations. It emphasizes a specific effect of the residential area on employment: the fact that the employment situation of people in the neighborhood has a direct effect on finding a job. Much databases do not provide sufficient information to investigate peer effects. Such an approach of the neighborhood endogenous social effect on getting a job can be view as a way to approximate local peer effects. In this paper, we more specifically investigate the link between the employment situation in the residential area they lived in when they finish school and their employment situation (having a job or not) three years after. Estimations are conducted on representative samples of 60,000 youth leaving the French educational system in 2001 and 2007: the 1998 and 2004 *Génération* surveys collected by Céreq (the French Center for Research on Education and Employment). Focusing on this specific working population group may partly prevent the endogeneity of residential location with job location. The location at that time is mainly driven by the choice of education and parents' choice of location, as most of them still live with their parents. Moreover, information about the respondent's residential location at the time he left school were recently added at a precise level. It gives the opportunity to have detailed information about the place of residence at an infra-municipality level by introducing contextual variables such as employment indicators. This detailed delineation of the location also enables us to use various definition of neighborhood in urban areas by gathering more or less extended nearby areas.

The rest of the paper proceeds as follows. Section 1 presents the estimation strategy. Section 2 describes how the spatial approach of employment variations is applied in practice using the

Génération databases and additional contextual variables. This summary of the data set provided the various definitions of neighborhoods that are used. Section 4 presents the results of both estimation methods carried out for men living in urban areas. The general finding is that local peers employment situation matters to enter job market: a one percentage point higher value of the local level of employment would increase the chance of getting a job by 0.22 (second method) to 0.45% (first method). The discussion that follows questioned the interpretation of these results. The case of employment gap between African immigrants and natives' children is used as a field of application.

1 Model

Following Brock and Durlauf (2001) and Brock and Durlauf (2007), we model employment of individual i living in neighborhood $g(i)$ as a binary variable $y_{ig(i)}$ that equals 1 if the individual is employed:

$$y_{ig(i)} = \mathbb{1}_{\{X_i\beta_1 + Y_{.g(i)}\beta_2 + Z_{.g(i)}\beta_3 + \varepsilon_{ig(i)} > 0\}}$$

where X_i a vector of individual observable characteristics, $Y_{.g(i)}$ and $Z_{.g(i)}$ are respectively an employment indicator and a vector of characteristics of the neighborhood.

We consider endogeneity of the social interaction effect when $Y_{.g(i)}$ is correlated to $\varepsilon_{ig(i)}$. The existence of endogeneity is natural if there exists sorting on unobserved heterogeneity in the location choice process. To correct for this problem of endogeneity, we propose two distinct strategies of identification. First, we find exogenous variation to explain the endogenous variable $Y_{.g(i)}$ following Evans, Oates, and Schwab (1992). The second strategy of identification consists in considering that agents choose a neighborhood but may be randomly allocated within the neighborhood as in Bayer, Ross, and Topa (2008). Several definitions of neighborhoods are used, each with enough people so that each agent could ignore the effect of his own choice on the average choice level calculated from the census.[2]

1.1 Instrumenting for the level of employment in the neighborhood

Evans, Oates, and Schwab (1992) use this framework to explore the link between teenage behaviors and school composition. Given that teenagers or parents may choose their high-school according to this criteria, they use city level variables to instrument the composition of the school. The motivation for these instruments is that families are not mobile between cities and are constrained to choose a school within a city, thus city characteristics may affect school composition, but may not directly impact teenage behaviors. The correction of the estimates by the instrumental variables method reduces the impact of school composition on teenage behaviors, suggesting that what we observe as an endogenous social effect is in fact the result of the teenagers similarity in terms of unobservable heterogeneity: self-selection remains an important issue when taking into account

[2]For a discussion about equilibrium properties and its uniqueness, see Tamer (2003) and Soetevent and Kooreman (2007).

social interactions. In the case of employment, estimations using epidemiological spatial models by Topa (2001) and Conley and Topa (2007) also show that there exists an important dependance between close neighborhoods. A similar instrumental variables strategy can be used if we assume that individuals are directly affected by the employment rate in his neighborhood, but that rates in other neighborhoods do not directly affect his employment outcome.

We first model the contextual variable $Y_{.g(i)}$ as a function of close neighborhoods, $g'(i)$, outputs: $Y_{.g(i)} = f(Y_{.g'(i)}, v_g)$. Works by Topa (2001) and Conley and Topa (2007) previously mentioned, show that the rank condition is likely to be satisfied. Adjacent areas share a common structure in terms of labor markets that implies an important correlation between employment rates. The exogeneity of instruments is verified if individuals living in a given neighborhood are not directly affected by the context of other neighborhoods. In terms of social interactions, this assumption holds if individuals' ties are randomly distributed among other neighborhoods.

Although it is not possible to verify this assumption, we check that the results are robust when using different distance and size of neighborhoods: individuals are less likely to be directly affected by further away neighborhoods but neighborhoods in a given city always share the same structure.

Estimation is achieved using usual maximum likelihood and two stage methods for the Probit model with endogenous covariates. The first stage is given by :

$$Y_{.g(i)} = X_i\gamma_1 + Z_{.g(i)}\gamma_2 + Y_{.g'(i)}\gamma_3 + v_{g(i)}$$

1.2 Random assignment within the neighborhood

In a second strategy of identification, we make the assumption that individuals choose a broad area where to live but that the precise neighborhood where they end up living is randomly assigned within this area. Bayer, Ross, and Topa (2008) use this assumption taking block assignments as random within a given neighborhood. This assumption allows to estimate the impact of neighborhood characteristics if we observe sufficient variation in neighborhood characteristics within the broader areas.

The assumption is sustained by the fact that individuals are likely to choose to live in a given neighborhood but that their final location is subject to random events such as the availability of empty accommodations at the moment they are looking for a place to live.

We still denote by $g(i)$ the neighborhood chosen by the individual. Within this neighborhood, we distinguish ℓ_g smaller locations and the final location where individual i lives is denoted by $\ell_{g(i)}$. Then individual outputs of the initial specification can be rewritten as :

$$y_{i\ell_{g(i)}} = \mathbb{1}_{\{X_i\beta_1 + Y_{.\ell_{g(i)}}\beta_2 + Z_{\ell_{g(i)}}\beta_3 + \varepsilon_{i\ell_{g(i)}} > 0\}}$$

where the residual $\varepsilon_{i\ell_{g(i)}}$ can be decomposed to take into account for the potential sorting process among broader areas:

$$\varepsilon_{i\ell_{g(i)}} = \alpha_{g(i)} + u_{i\ell_{g(i)}}$$

where we assume $u_{i\ell_{g(i)}}$ independent of covariates.

The estimation of this specification is achieved by assuming that $u_{i\ell_{g(i)}}$ are type I extreme values with Gumbel distribution. This particular distribution allows to differentiate out the fixed effects $\alpha_{g(i)}$ without affecting estimations. The model used is then a logit model.

2 Data

2.1 *Génération* surveys

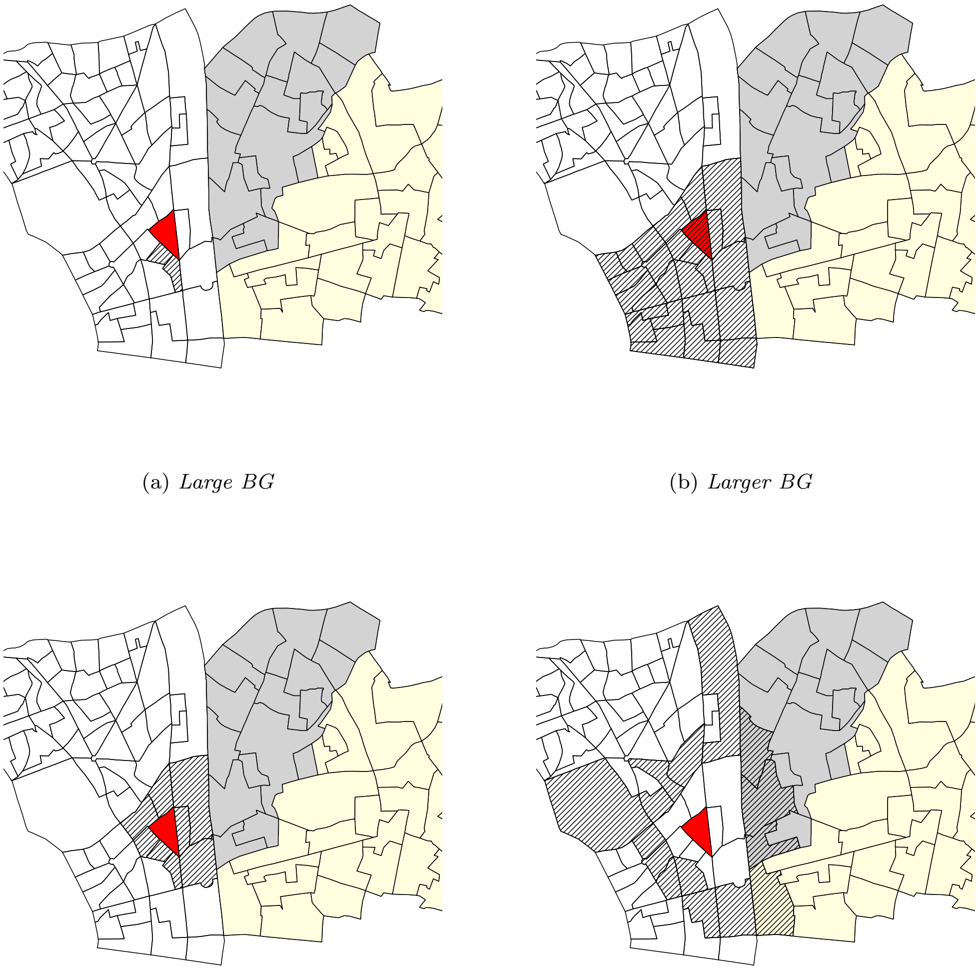
To estimate the model, we used data from the *Génération* surveys collected by Céreq (the French Center for Research on Education and Employment). These surveys are representative samples of young people who leave the French educational system for the first time in a given year. These young people are interviewed three years after they leave school. In addition to the information relative to their labor market situation, the *Génération* surveys include many respondent's characteristics: family's socioeconomic status, age, education, household situation, parents' place of birth and nationality at birth... We use the surveys conducted in 2001 and 2007 on the 1998 and 2004 cohorts in which geolocation data have been recently added.

In both surveys, the respondent's infra-municipality residential location at the time he left school is provided: location is known at the census statistical block groups (*IRIS*) level. These small geographic areas are used by the French national institute of statistics (INSEE) for the dissemination of local data, especially within the almost 1,900 urbanized municipalities with more than 5,000 inhabitants[3]. Their target size is 2,000 inhabitants and their actual population generally falls between 1,800 and 5,000. Each *IRIS* unit is defined to be *"homogeneous in terms of living environment and the boundaries of the unit are based on the major dividing lines provided by the urban fabric (main roads, railways, bodies of water etc.)"*[4]. Including *IRIS* units in the municipality framework, the number of delineated areas in metropolitan France increases from 36,000 to almost 50,000. We will refer to *IRIS* as *Block Groups (BG)*. The residential location of an individual will refer to the *BG* he lives in as it is the smallest delineated area.

Larger areas aggregating *Block Groups (BG)* can also be used within municipalities. *TRIRIS* are the next level above *BG* in the geographic hierarchy: each *TRIRIS* is a combination of *BG* (in general three *IRIS*). *Large Districts* (*"Grands quartiers"*) are a level even above clustering *TRIRIS*. Like IRIS, both are defined so that each delineated unit is homogenous. We will refer to these two types of within municipality areas as *Large BG* and *Larger BG*. By default, analysis is restricted to areas delineated in *BG* excluding rural municipalities with less than 5,000 inhabitants.

Figure 1 gives an illustration of these perimeters. On these maps, all nuclear divisions refer to *Block Groups (BG)*. Consider an individual located in the *BG* represented in red.[5] On Figure 1a, the dashed area corresponds to the *Large BG* where he lives while the dashed area on Figure 1b corresponds to his *Larger BG*. The area of the municipality he belongs to (Paris in this example)

[3] *IRIS* are delineated in all municipalities with more than 10,000 inhabitants and in most with more than 5,000.
[4] http://www.insee.fr/en/methodes/default.asp?page=definitions/iris.htm
[5] Shaded area for black and white copies.



(a) *Large BG* (b) *Larger BG*

(c) First surrounding belt (N1) (d) Second surrounding belt (N2)

Figure 1: Alternative definitions of neighborhoods: Block Groups (BG), cluster BG and surrounding belts.

is also partially represented by the white area surrounding the delineations previously mentioned, by opposition to the grey and yellow tint areas[6] belonging to other municipalities (respectively Bagnolet and Montreuil).

2.2 Contextual variables

Contextual variables are matched to the survey through the *BG*. We import data from several sources of information. By default, local employment rates are taken from the 1999 exhaustive census for the 1999 cohort and from the 2006 census[7] for the 2004 cohort. Census also provide information on the neighborhood social composition at the *BG* level (number of blue collar workers,

[6]East-half darker areas for black and white copies.
[7]Based on the 2004-2008 Permanent census survey.

immigrants, single-mother families...). The first "Permanent database of facilities" (BPE)[8] is used to get detailed information about facilities and services existing in each *BG*.[9] It provides information about the diversity and quantity of various facilities in the immediate surroundings. We know if there are any police stations, general practitioners, pharmacies, child care services, hairdressers, professional builders / repairs, post offices, banks, local retailers (such as backer, butcher and grocer shops, newspaper stores...), shopping centers, sport facilities (indoor/outdoor), cinema... Contextual variables calculated from the 2006 census are also added giving information about the type of housing (public housing ratio, the single-detached dwellings ratio), the homeownership status, residents turnover (proportion of residents in the block since at least 5 years / arrived during the two last years), transport mode (car owner ratio, public transportation ratio) and the social composition of the block (ratio executive/white and blue collar, proportion of people without diploma, one parent family ratio, immigrant-to-population ratio). Available for each *BG*, all this information can also be gathered at any cluster level such as *Large BG* and *Larger BG*.

2.2.1 Distance between areas and surrounding belts of instrumentation

For each individual, the neighborhood where he lives in when he left school is denoted as $g(i)$. As in Topa (2001), we consider the distance $d(g, g')$ between two neighborhoods g and g' as the minimum number of frontiers an individual has to cross to go from g to g'. For individual i we denote by $g_1(i)$ the set of neighborhoods such that $g_1(i) = \{g : d(g(i), g) = 1\}$. It is the area of the *BG* that immediately encircle the *BG* of residence. They delimit a first surrounding belt. More generally, we define $g_k(i) = \{g : d(g(i), g) = k\}$ as the k^{th} surrounding belt. Back to Figure 1, for individual i situated in the red *BG*, $g_1(i)$ corresponds to the dashed area on Figure 1c and $g_2(i)$ corresponds to the dashed area on Figure 1d. Then, the covariate that gives the employment rate in the area of residence is denoted by $y_{.g(i)}$, and instruments, that is the employment rate in other locations, are denoted by $y_{.g_1(i)}$.

2.2.2 Nested neighborhoods and exogenous location

For the second strategy of identification, we consider *Large BG*, *Larger BG* and even municipalities as potential neighborhoods chosen by the individual and thus as perimeters on which sorting may play an important role. Within these neighborhoods, we use the variation from one *BG* to another in order to identify the effect of local neighborhood characteristics. Focusing on the previous maps (Figures 1a and 1b), we will then assume that an individual chose to live in the dashed area but that his location in a specific *BG* within this area is random.

[8] A detailed description of this 2007 database is given at http://www.insee.fr/en/methodes/default.asp?page=sources/ope-adm-bpe.htm

[9] The "Municipalities Inventories 1998" fits better in terms of the time of data collection but brings no information about infra-municipalities variations. We assume that despite a 8-year distance, these contextual variables can be used as indicators.

2.3 Data overview

2.3.1 Characteristics of the selected sample

This study is devoted to identify local social effects in finding a job. For that purpose, we choose to disentangle this specific effect from the correlation existing between an individual's location of residence when he finishes school and his employment situation three years after. For more homogeneity in the type of residential areas and to be able to use various homogenous definition of neighborhood, estimation are conducted on areas delineated in BG, excluding municipalities less than 5,000 inhabitants. Youth living outside Metropolitan France just before high school are also excluded to prevent education variables to be affected by a primary education in a foreign country. To ensure the results are not driven by extreme values, the distribution of youth according to their BG employment ratio is truncated at 1st and 99th percentile. Table 1 includes tabulated data for both this selected sample and the whole survey sample, the size of the subsample being slightly above half of sample.

The positive correlation between the level of employment where an individual lived when he finished school and his employment situation three years after can be observed Figure 2a. BG ratio of employment for 15-24 year olds are calculated from the 1999 census for the 1998 cohort and from the 2006 census for the 2004 cohort. The proportion of youths having a job increases with the levels of employment in their BG of residence when they finished school. It increases by 18% between BG areas with the lowest and the highest level of employment.[10] Spatial sorting might explain such a relation even if the sample partly prevent from the direct effect of job location on residential location. The location of youths finishing school is mainly driven by an education choice and parents' choice of location, as most of them still live with their parents when they finished school: three quarters of men are in such a situation (see Table 1). But as educational achievement is linked with family background, residential sorting affecting parents may cause an educational sorting of their children. That could explain the positive relation between the local level of employment and the probability of finding a job three years after. However, the positive correlation can still be observed for subsamples having the same level of education (Figure 2b), even if this relation is stronger for the less educated youths.[11] The purpose of the next parts of the paper is to carry on and check if such a correlation still exists after controlling for other individual characteristics, local amenities and potential endogeneity.

2.3.2 Individual characteristics control variables

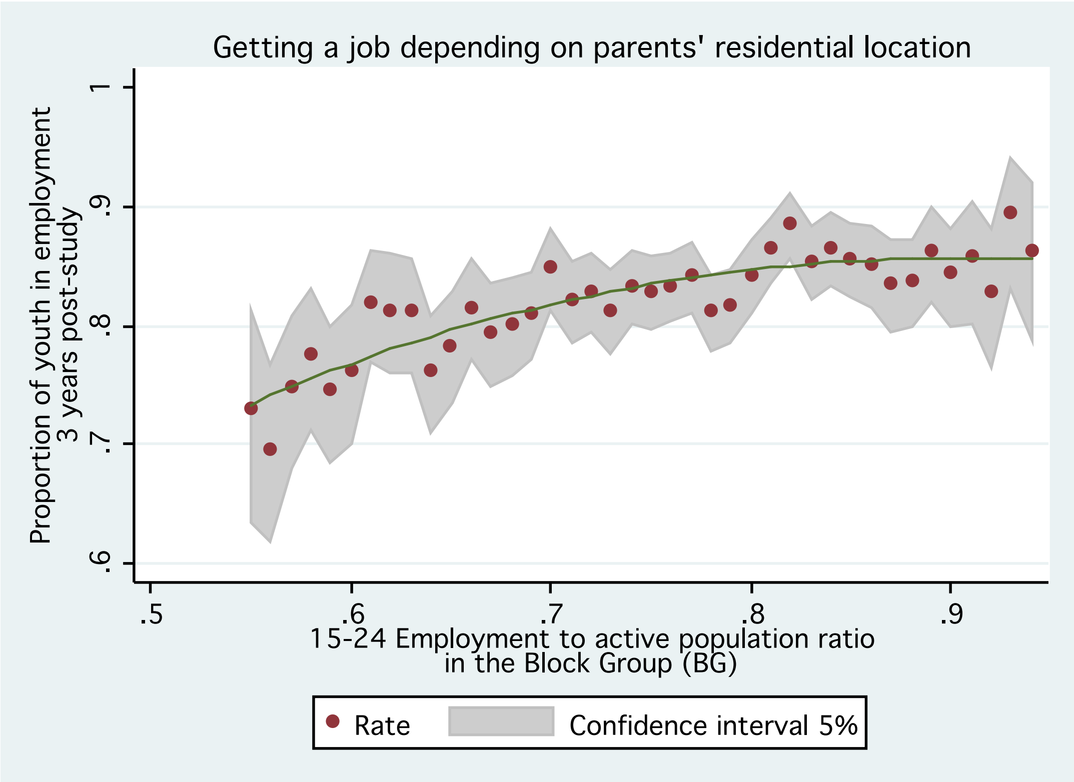
Several individual characteristics are used as control variables in the following analysis. The level of education is controlled by making a distinction between six levels of education. Respondents having repeated a class before high school are also identified and their age at the end of education is introduced (according to the level of education they have attained). Characteristics of the parents

[10] Respectively 55% and 94% BG ratio of employment for 15-24 year olds on Figure 2a as the distribution is truncated at 5st and 95th percentile to avoid too large to large confidence interval on the chart.

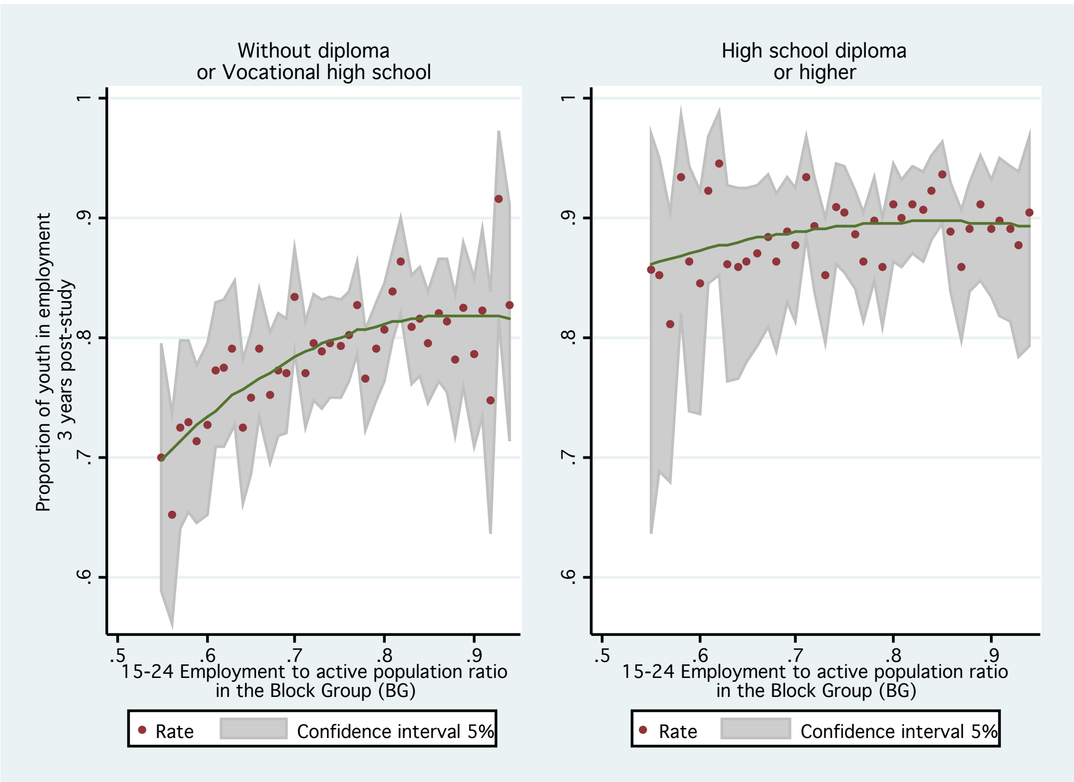
[11] A similar correlation can be observed using employment ratios for 15-64 year olds see in Appendix Figure 3.

	Studied Sample		Whole population	
	Men	Women	Men	Women
Employed (%)	84.1	81.66	85.4	82.7
Mean age (end of education)	21.9	22.6	21.3	22.3
Education (%)				
Repeating a year before high-school	21.8	13.7	22.9	13.7
No diploma	18	8.8	18.3	8.4
Vocational high-school	19.6	9.2	24.3	11.1
General high-school	19.8	20.9	21.6	23
Higher vocational	12.6	22.3	13	26.2
College	12	22.8	9.2	18.8
Graduate	18	16	13.6	12.5
Socio-economic status of parents (%)				
Blue/white-collar	51.8	50.2	53	51.6
Intermediate	10	9.7	9.9	9.4
Executive	25.9	27.3	21.9	23.4
Craftsman	12.3	12.9	15.1	15.6
Parents' occupation				
Two working parents	54.9	56	58.3	59.5
One working parent	27.8	27.3	26.3	25.5
Never work/unknown parent	17.3	16.7	15.4	15.1
Parents' foreign origin				
Immigrant parent	17.2	14.8	12.8	11.1
incl.: from African c.	8.6	7.6	5.8	5.3
Rapat/Expat parent	5.3	6.6	4.2	5
incl. from Maghreb	3.9	5.1	2.9	3.7
Household (%)				
Parental home	70.3	58.5	74.3	60.7
Living in couple	14.5	24.8	11.8	24
Single	15.2	16.7	13.9	15.4
Having children	9.2	17.5	7.6	17.1
Past residential immobility				
Same municipality	87.1	84.5	89.9	87.5
Immobility duration (years)	9	9.5	8.8	9.6
Generation 2004 (%)	27.1	24.1	34.4	30.1
Delineated in *BG*	100	100	55.4	58.8
N	16 695	16 236	31270	29 073

Table 1: Characteristics of youth finishing school in 1998 and 2004



(a) *All men*



(b) *By level of education*

Figure 2: Level of employment where an individual lived when he finished school and his employment situation three years after

are also taken into account. Their foreign origin is used to make a distinction between three groups: individuals having two parents born in France, individuals having at least one immigrant parent[12], individuals having at least one parent born in a foreign country with the French nationality.[13] Socio-economic status of parents is taken into account by making a distinction between a reference group having blue/white-collar parents and three other groups for youths with at least one of their parent occupation being intermediate, executive or craftsman. The occupation status of the parents is ranking from the case of two working parents to the case of parents who never worked (or are unknown) including cases of one working parent and of one parents who never work. When they left school, individual can live with their parents or on their own either as a single or a couple. A dummy variable indicates if respondents became a parent during the first three years after leaving school. Past residential mobility during education is also computed. We can know if an individual were in the same municipality when they began high school and when they left school (and the duration of this likely residential immobility, which correspond to youths who had not left their parents' home). As we use both *Génération* surveys from 1998 and 2004, a dummy variable for the 2004 cohort respondents is added. Descriptive statistics for all these variables are provided Table 1.

2.3.3 Neighborhood characteristics

The local situation of employment is introduced through the 15-24 employment-to-active population ratio. Other ratios are also used, calculated with other denominators (such as employment-to-population ratio) or on all ages (15-64 year olds).

The other contextual characteristics are summed-up into 4 variables using principal component analysis and multiple correspondence analysis. As contextual variables are highly correlated, this strategy enables us to reduce the dimensionality of data while maintaining enough information to control for most of the neighborhood characteristics. We use two different types of projections as variables coming from each source (Census and "Permanent database of facilities" (BPE)) are quite different. 11 rates from the census give information about the type of housing and neighbors whereas 17 dummies from the "Permanent database of facilities" (BPE) indicate the existence of various services and facilities in the neighborhood. The three first axes of the principal component analysis account for three-quarters of the total variance. The first axe splits BG according to the type of housing (high rate of public housing in the positive part versus high rate of single-detached dwelling owners in the negative part). The social composition of the BG is projected on the second axis: areas with high proportions of executives and newcomers (in the block since for less than 2 years) are on the negative part whereas areas with the highest levels of immobile residents (in the block since at least 5 years) without any diploma are on the positive part. The positive part of the third axis mainly distinguishes areas where residents are mainly immobile, executives and use public transportation. Residential areas are also sorted in descending order of local services and

[12] An additional distinction in made for immigrants from African countries.

[13] With a specific distinction for those born in Maghreb, the former main french colony of settlement.

facilities on the first dimension of the multiple correspondence analysis. It accounts for almost 90% of the inertia.

3 Results

3.1 Estimation framework

In the following estimation approaches, we try to estimate local peer effects on entering the job market. Employment situation is defined as being or not in employment at the time of the survey three years after leaving school. Estimations are conducted on urban municipalities delineated in statistical *Block Groups (BG).* Various employment ratios are used as a proxy of peers employment situation in the neighborhood such as employment-to-active population ratios (Empl/act) and employment-to-population ratios (Empl/pop). They are calculated for different age groups and on larger or smaller neighborhood areas. The other characteristics of the *BG* of residence are taken into account through their projection on the three axes.

The two approaches do not share exactly the same spatial support, the second excluding some observations used in the first one. In the second approach, fixed effects take into account the characteristics of the neighborhood including peers level of employment. Within each BG cluster (such as *Large BG* and *Larger BG*), variations of these local characteristics are measured as in the first approach. A necessary condition for estimation is that all surveyed inhabitants living in a given neighborhood (BG cluster) do not have similar outcomes, otherwise local fixed effect cannot be estimated. Thus, the spatial support will be limited to large and various neighborhoods where at least two surveyed youth with different outcomes (in employment or not) can be observed.

3.2 Instrumenting by the level of employment in the surrounding belt areas

The *BG* 15-24 employment-to-active population ratio is instrumented by different indicators of employment conditions in various surrounding areas. We first use the average employment situation in abutted *BG*. This first *BG* belt called N1 (also defined previously as a $g_1(i)$ area type) immediately surrounds the given *BG*. Estimations using the second belt (the abutted *BG* of the first belt) are also conducted (Table 2). Larger belts clustering surrounding *Large BG* and *Larger BG* (rather than simple *BG*) are also used to test the robustness of the results to spatial change. Table 2 and 4 show the impact of the employment rate in the employment equations using these various instruments. From a general point of view, all estimates are slightly higher than one and significantly different from 0. The use of instruments tends to increase the value of the coefficients in comparison with the value of the coefficient obtained without instrumenting.

The results are robust to the choice of instrument. In Table 2, we can observe that the results do not change much when we choose distant neighborhoods (ie the second belt N2 rather than the first belt N1) to instrument the local peers employment indicator. From the last two columns of

Table 2: Men employment probit and IV probit: estimated coefficients of the neighborhood employment ratio

Employment	Probit	IV Probit	IV Probit	IV Probit	IV Probit
15-24 Empl/act	1.0120***	1.7837***	1.9307***	1.8672***	2.0674***
	(0.1439)	(0.2707)	(0.2774)	(0.3202)	(0.3446)
15-24 Empl/act IV Probit 1^{st} stage		OLS	OLS	OLS	OLS
15-24 Empl/act N1		0.6250***			
		(0.0109)			
15-24 Empl/act N2			0.6506***		
			(0.0124)		
15-64 Empl/act N1				0.8219***	
				(0.0203)	
15-64 Empl/act N2					0.7924***
					(0.0225)
N	16 610	16 610	16 610	16 610	16 610

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

Table 3: Men employment probit and IV probit: marginal effects of the neighborhood employment ratio

Employment	Probit	IV Probit	IV Probit	IV Probit	IV Probit
15-24 Empl/act	0.2442***	0.4314***	0.4673***	0.4518***	0.5009***
	(0.0347)	(0.0661)	(0.0680)	(0.0785)	(0.0848)
N	16 610	16 610	16 610	16 610	16 610

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 4, we can see that our results are robust when using larger areas (ie *Large BG* and *Larger BG* rather than *BG*) to create our instrument. Finally, we can observe in both tables that the results do not depend on the choice of the instrument in terms of age: whether we use the employment rate for individuals aged between 15 and 24 or for individuals aged between 15 and 64 does not have a significant impact on the results.[14]

Corresponding marginal effects of the *BG* 15-24 employment-to-active population ratio (with and without instrumenting) are computed Table 3 and Table 5. The estimated elasticity of the chance of getting a job with respect to the local 15-24 Empl/act rate is ranged from 0.24 (before correction) to 0.45. It means that a 1 point of percentage higher level of *BG* employment ratio would be associated with an increase in the chance of getting a job by one-quarter to one-half of a percent.

[14] Using *BG* employment rate from 1999 even for the 2004 cohort do not change the result (see in Appendix Table 8 and the followings): the *BG* 15-24 employment-to-active population ratio has still an impact on employment.

Table 4: Men employment probit and IV probit: estimated coefficients of the neighborhood employment ratio

Employment	Probit	IV Probit	IV Probit	IV Probit	IV Probit
15-24 Empl/act	1.0120***	1.5872***	1.5171***	1.7036***	1.7040***
	(0.1439)	(0.2263)	(0.2323)	(0.2863)	(0.2938)
15-24 Empl/act IV Probit 1^{st} stage		OLS	OLS	OLS	OLS
15-24 Empl/act *Large BG* N1		0.8004***			
		(0.0103)			
15-24 Empl/act *Larger BG* N1			0.7823***		
			(0.0105)		
15-64 Empl/act *Large BG* N1				0.9809***	
				(0.0206)	
15-64 Empl/act *Larger BG* N1					0.9481***
					(0.0210)
N	16 610	16 610	16 610	16 610	16 610

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

Table 5: Men employment probit and IV probit: marginal effects of the neighborhood employment ratio

	Probit	IV Probit	IV Probit	IV Probit	IV Probit
15-24 Empl/act	0.2442***	0.3835***	0.3665***	0.4119***	0.4120***
	(0.0347)	(0.0551)	(0.0564)	(0.0699)	(0.0717)
N	16 610	16 610	16 610	16 610	16 610

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01*

3.3 Nested neighborhood, fixed effects and within exogenous variations of local employment situation

In the second estimation strategy, neighborhood (cluster BG) characteristics are controlled using fixed effects. By default, neighborhood is the *Larger BG* but estimations are also computed using smaller *Large BG* and larger *Municipality* neighborhood areas.[15] Peer employment variations within the neighborhood are assumed to be exogenous. Other variations in social composition and amenities within the neighborhood are controlled for using the projections of these characteristics on their three principal components and are assumed to be exogenous too.

Local variations of the 15-24 Employment-to-active population ratio within BG each neighborhood still have a significant impact on employment (Table 6). The chance of having a job rather than being unemployed are supposed to be from 3 to almost 5 times higher in a BG without any unemployed people rather than one without any employed people.[16] In other terms, for a one-unit increase in the very local ratio[17], we would expect to see an increase in the odds of being employed ranging from 1.1% to 1.6% . Marginal effects can be calculated at the mean value of the ratio in the model with no fixed effects (Table 7). A 1 percentage point increases in the BG employment ratio would induce a 0.22% increase of the chance of getting a job.

Table 6: Effect of Intra-*Larger BG* variation of employment: Men employment logit

Employment	Logit (*Larger BG* FE)	Logit (*Larger BG* FE)	Logit (*Larger BG* FE)
15-24 Empl/act	1.1110***		
	(0.4185)		
15-24 Empl/pop		1.1440**	
		(0.5251)	
15-64 Empl/act			1.5816*
			(0.8278)
N	10,960	10,960	10,960

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

[15] See Appendix from Table 13 to Table 16.

[16] Table 6 values are also the expected change in log odds with an employment ratio are ranged from 0 to 1. Odd ratio are obtained taking their exponential value.

[17] For one percentage point increase in this ratio, coefficients in Table 6 are divided by 100.

Table 7: Marginal effect of Intra-*Larger BG* variation of employment (FE=0): Men employment logit

Employment	Logit (*Larger BG* FE)	Logit (*Larger BG* FE)	Logit (*Larger BG* FE)
15-24 Empl/act	0.2257***		
	(0.0569)		
15-24 Empl/pop		0.2790**	
		(0.1240)	
15-64 Empl/act			0.2353***
			(0.0268)
N	10,960	10,960	10,960

*Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq). Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

3.4 Discussion

3.4.1 Interpretation of the results

The aim of this paper is to identify the effect of the neighborhood employment level on youth employment. We attempt to address the potential endogeneity of the local level of employment using two different methods. Both rely on strong but different hypothesis. Estimates from both methods show that the chance for a youth to get a job depends on his neighborhood employment level, especially the 15-24 employment-to-active population ratio. A one percentage point higher value of the local level of employment would increase the chance of getting a job by 0.22 (second method) to 0.45% (first method). These results suggests the existence of a social multiplier effect: each youth having a job rather than being unemployed increases the relative chance of his youth neighbors to get a job. This paper is also an indirect approach of peer effects through the territory as we neither have information about the actual network of each individual nor about the type of interaction.

First, we assume that people are influenced by the people of their age living in their residential area at the time they finished school. In most case, it is the area they grown-up. So we can suppose that they actually had interactions attending the same primary school (due to school catchment area), having similar recreational activities (sport clubs), patronizing the same places, seeing each other in the street... The situation of these peers may have a lasting influence on an individual as friends, acquaintances, role models... Parents can also be a channel of their influence holding up the situation of these familiar youths as an example.

Second, we use a quite agnostic empirical approach of the neighborhood. Focusing *BG* delineated areas give us the opportunity to define neighborhood areas depending on few homogenous blocks rather than on larger administrative boundaries. Moreover, this detailed delineation of the location also enables us to use various definition of neighborhood by gathering more or less extended nearby areas.

No matter what specific definition of the neighborhood is chosen, estimates highlight a significant effect of youth neighbors employment situation on the chance of getting a job. The effect remains significant even after controlling by two different methods for potential endogeneity of local employment levels. Further analysis show that this effect can be affected by some individual characteristics. Indeed, crossed effect of employment rate and some variables vary between modalities. For example, the level of employment in the BG has a stronger additional impact on youths without diploma (see in Appendix Table 20). But most of these crossed effects remained non significant at the 10% level.

4 Conclusion

This paper is devoted to studying local peers effect on entering job market. We test the hypothesis that employment status of the peers in the neighborhood has an effect on getting a job. Two estimation strategies are used to disentangle the local peer effect from local residential sorting. The first one use surrounding employment conditions to instrument neighborhood level of employment. The second one relies on the assumption of random assignment within the neighborhood. Estimates from both strategies suggest that the local employment situation of youths does matter to enter job market. It reveals the existence of a social multiplier effect suggesting the local positive externalities of employment on employment. This result do not provide a clear channel policy makers can use to improve job access. However, it can give some clues for further investigations on the local effect of subsidized job or on spatially targeted employment policies.

A Appendix

A.1 Descriptive statistics

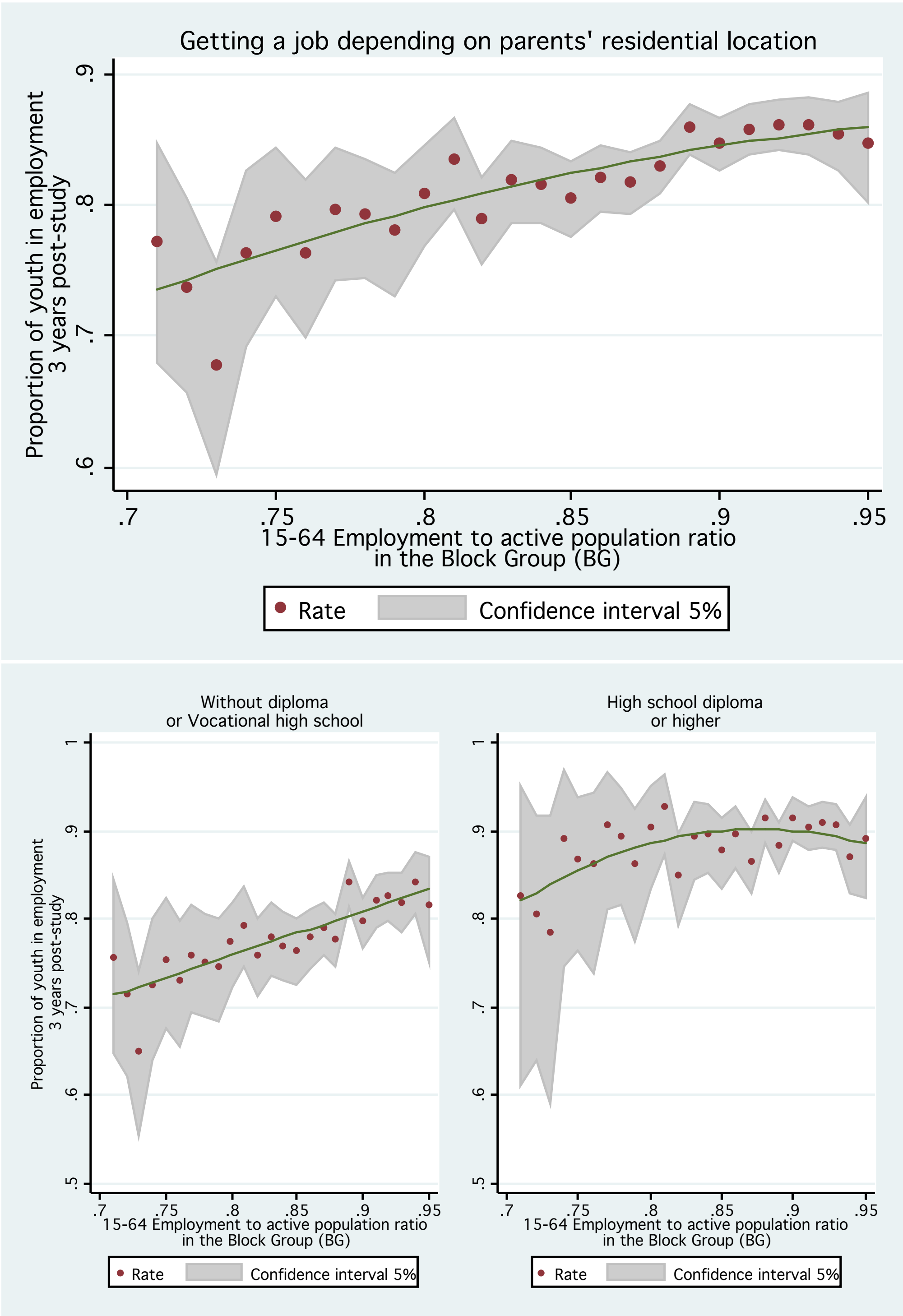


Figure 3: Level of employment where an individual lived when he finished school and his employment situation three years after

A.2 Instrumental approach

A.2.1 Using employment level in 1999 (for all)

Table 8: Men employment probit and IV probit: estimated coefficients of the neighborhood employment ratio in 1999

Employment	Probit	IV Probit	IV Probit	IV Probit	IV Probit
15-24 Empl/act	1.1269***	1.5815***	1.6336***	1.6648***	1.8942***
	(0.1420)	(0.2394)	(0.2490)	(0.2813)	(0.3034)
15-24 Empl/act IV Probit 1^{st} stage		OLS	OLS	OLS	OLS
15-24 Empl/act N1		0.6787***			
		(0.0113)			
15-24 Empl/act N2			0.6961***		
			(0.0127)		
15-64 Empl/act N1				0.8886***	
				(0.0206)	
15-64 Empl/act N2					0.8554***
					(0.0228)
N	16,610	16,610	16,610	16,610	16,610

*Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq). Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

Table 9: Men employment probit and IV probit: marginal effects of the neighborhood employment ratio in 1999

Employment	Probit	IV Probit	IV Probit	IV Probit	IV Probit
15-24 Empl/act	0.2717***	0.3816***	0.3942***	0.4018***	0.4576***
	(0.0343)	(0.0581)	(0.0605)	(0.0684)	(0.0741)
N	16,610	16,610	16,610	16,610	16,610

*Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq). Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 10: Men employment probit and IV probit: estimated coefficients of the neighborhood employment ratio in 1999

Employment	Probit	IV Probit	IV Probit	IV Probit	IV Probit
15-24 Empl/act	1.1269***	1.4865***	1.4310***	1.6077***	1.6074***
	(0.1420)	(0.2071)	(0.2116)	(0.2550)	(0.2619)
15-24 Empl/act IV Probit 1^{st} stage		OLS	OLS	OLS	OLS
15-24 Empl/act triris N1		0.8321***			
		(0.0105)			
15-24 Empl/act gquart N1			0.8153***		
			(0.0108)		
15-64 Empl/act triris N1				1.0390***	
				(0.0209)	
15-64 Empl/act gquart N1					1.0067***
					(0.0213)
N	16,610	16,610	16,610	16,610	16,610

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

Table 11: Men employment probit and IV probit: marginal effects of the neighborhood employment ratio in 1999

	Probit	IV Probit	IV Probit	IV Probit	IV Probit
T1524_iris_N0_99	0.2717***	0.3586***	0.3451***	0.3879***	0.3878***
	(0.0343)	(0.0502)	(0.0513)	(0.0620)	(0.0636)
N	16,610	16,610	16,610	16,610	16,610

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

A.2.2 Alternative output: permanent contract

Table 12: Men permanent work contract probit and IV probit: estimated coefficients of the neighborhood employment ratio (*Block Group* level)

Permanent contract	Probit	IV Probit	IV Probit	IV Probit	IV Probit
15-24 Empl/act	1.1619***	2.0323***	1.9687***	2.4142***	2.1941***
	(0.1231)	(0.2292)	(0.2383)	(0.2725)	(0.3005)
15-24 Empl/act IV Probit 1^{st} stage		OLS	OLS	OLS	OLS
15-24 Empl/act N1		0.6250***			
		(0.0109)			
15-24 Empl/act N2			0.6506***		
			(0.0124)		
15-64 Empl/act N1				0.8219***	
				(0.0203)	
15-64 Empl/act N2					0.7924***
					(0.0225)
N	16,610	16,610	16,610	16,610	16,610

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

A.3 Nested neighborhood

A.3.1 Intra-Municipality and *Large BG* variation of employment

Table 13: Effect of Intra-Municipality variation of employment: Men employment logit

Employment	Logit (Mun. FE)	Logit (Mun. FE)	Logit (Mun. FE)
15-24 Empl/act	0.9348***		
	(0.3540)		
15-24 Empl/pop		0.6070	
		(0.4255)	
15-64 Empl/act			1.5989**
			(0.6667)
N	13,655	13,655	13,655

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

Table 14: Marginal effect of Intra-Municipality variation of employment (for FE=0): Men employment logit

Employment	Logit (Mun. FE)	Logit (Mun. FE)	Logit (Mun. FE)
15-24 Empl/act	0.2018***		
	(0.0582)		
15-24 Empl/pop		0.1504	
		(0.1043)	
15-64 Empl/act			0.2377***
			(0.0227)
N	13,655	13,655	13,655

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

Table 15: Effect of Intra-*Large BG* variation of employment: Men employment logit

Employment	Logit (*Large BG* FE)	Logit (*Large BG* FE)	Logit (*Large BG* FE)
15-24 Empl/act	1.1572**		
	(0.4497)		
15-24 Empl/pop		0.8781	
		(0.5683)	
15-64 Empl/act			1.3918
			(0.9435)
N	9,538	9,538	9,538

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

Table 16: Marginal effect of Intra-*Large BG* variation of employment (FE=0): Men employment logit

Employment	Logit (*Large BG* FE)	Logit (*Large BG* FE)	Logit (*Large BG* FE)
15-24 Empl/act	0.2446***		
	(0.0653)		
15-24 Empl/pop		0.2184	
		(0.1397)	
15-64 Empl/act			0.2471***
			(0.0605)
N	9,538	9,538	9,538

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

A.3.2 Using employment level in 1999 (for all)

Table 17: Effect of Intra-Municipality variation of employment (1999 rates): Men employment logit

Employment	Logit (Mun. FE)	Logit (Mun. FE)	Logit (Mun. FE)
15-24 Empl/act	1.1490***		
	(0.3878)		
15-24 Empl/pop		0.7220	
		(0.5465)	
15-64 Empl/act			1.9178***
			(0.6462)
N	13,655	13,655	13,655

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

Table 18: Effect of Intra-*Larger BG* variation of employment (1999 rates): Men employment logit

Employment	Logit (*Larger BG* FE)	Logit (*Larger BG* FE)	Logit (*Larger BG* FE)
15-24 Empl/act	1.4759***		
	(0.4797)		
15-24 Empl/pop		1.1608	
		(0.7310)	
15-64 Empl/act			2.0906**
			(0.8778)
N	10,960	10,960	10,960

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

Table 19: Effect of Intra-*Large BG* variation of employment (1999 rates): Men employment logit

Employment	Logit (*Large BG* FE)	Logit (*Large BG* FE)	Logit (*Large BG* FE)
15-24 Empl/act	1.6109***		
	(0.5449)		
15-24 Empl/pop		0.8148	
		(0.7814)	
15-64 Empl/act			1.7716*
			(0.9853)
N	9,536	9,536	9,538

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

A.3.3 Crossed effect of employment ratio and each level of education

Table 20: Effect of Intra-*Larger BG* variation of employment: Men employment logit

Employment	Logit (*Larger BG* FE)	Logit (*Larger BG* FE)	Logit (*Larger BG* FE)
15-24 Empl/act	1.3440**		
	(0.5450)		
*Voc. h. school	-0.1245		
	(0.6443)		
*Gen. h. school	-0.3476		
	(0.6192)		
*Higher vocational	-1.0576		
	(0.8542)		
*College	-0.1618		
	(0.8288)		
*Graduate	-0.2933		
	(0.9643)		
15-24 Empl/pop		1.9200***	
		(0.7388)	
*Voc. h. school		-0.7638	
		(0.8430)	
*Gen. h. school		-1.0451	
		(0.8164)	
*Higher vocational		-2.1573**	
		(1.0514)	
*College		0.0283	
		(1.0744)	
*Graduate		-1.5745	
		(1.0094)	
15-64 Empl/act			2.1346**
			(0.9367)
*Voc. h. school			-0.1141
			(0.9687)
*Gen. h. school			-1.5585*
			(0.9178)
*Higher vocational			-2.0862
			(1.5329)
*College			-1.3407
			(1.3302)
*Graduate			0.0467
			(1.4961)
N	10,960	10,960	10,960

Models estimated by ML using data from Generation 1998 and 2004 Surveys (Cereq).
*Clustered standard errors appear in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
Models also include controls for education level, repeating years before high school, cohort, age lefting school (by education level), type of household, children, past residential mobility, parents' socio-economic status, occupation and foreign origin, neighborhood amenities

References

Bayer, P., F. Ferreira, and R. McMillan (2007): "A Unified Framework for Measuring Preferences for Schools and Neighborhoods," *Journal of Political Economy*, 115(4), 588–638.

Bayer, P., S. L. Ross, and G. Topa (2008): "Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes," *Journal of Political Economy*, 116(6), 1150–1196.

Blume, L. E., W. A. Brock, S. N. Durlauf, and Y. M. Ioannides (2011): "Chapter 18 - Identification of Social Interactions," vol. 1 of *Handbook of Social Economics*, pp. 853 – 964. North-Holland.

Brock, W. A., and S. N. Durlauf (2001): "Discrete Choice with Social Interactions," *Review of Economic Studies*, 68(2), 235–60.

Brock, W. A., and S. N. Durlauf (2007): "Identification of binary choice models with social interactions," *Journal of Econometrics*, 140(1), 52–75.

Calvo-Armengol, A., and M. O. Jackson (2004): "The Effects of Social Networks on Employment and Inequality," *American Economic Review*, 94(3), 426–454.

Conley, T. G., and G. Topa (2007): "Estimating dynamic local interactions models," *Journal of Econometrics*, 140(1), 282–303.

Evans, W. N., W. E. Oates, and R. M. Schwab (1992): "Measuring Peer Group Effects: A Study of Teenage Behavior," *Journal of Political Economy*, 100(5), 966–91.

Gobillon, L., H. Selod, and Y. Zenou (2007): "The Mechanisms of Spatial Mismatch," *Urban Studies*, 44(12), 2401–2427.

International Labor Organization (2012): "Global Employment trends for Youth 2012," Report, International Labor Organization.

Ioannides, Y. M., and G. Topa (2010): "Neighborhood Effects: Accomplishments And Looking Beyond Them," *Journal of Regional Science*, 50(1), 343–362.

Manski, C. F. (1993): "Identification of Endogenous Social Effects: The Reflection Problem," *Review of Economic Studies*, 60(3), 531–42.

Nesheim, L. (2004): "Equilibrium Sorting of Heterogeneous Consumers Across Locations," Econometric Society 2004 North American Summer Meetings 337, Econometric Society.

Soetevent, A. R., and P. Kooreman (2007): "A discrete-choice model with social interactions: with an application to high-school teen behavior," *Journal of Applied Econometrics*, 22(3), 599–624.

Stutzer, A., and R. Lalive (2004): "The Role of Social Work Norms in Job Searching and Subjective Well-Being," *Journal of the European Economic Association*, 2(4), 696–719.

Tamer, E. (2003): "Incomplete Simultaneous Discrete Response Model with Multiple Equilibria," *Review of Economic Studies*, 70(1), 147–165.

Topa, G. (2001): "Social Interactions, Local Spillovers and Unemployment," *Review of Economic Studies*, 68(2), 261–95.