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Florence GOFFETTE-NAGOT, Marie Aurélie LAPIERRE

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Florence Goffette-Nagot[a] and Marie Aurélie Lapierre[b]

[a]Cergic, ENS de Lyon, CNRS, F-69007 Lyon, France. *florence.goffette-nagot@cnrs.fr.*
[b]Université Paris-Dauphine, Université PSL, LEDA, CNRS, IRD, 75016 Paris, France.
marie-aurelie.lapierre@dauphine.psl.eu.

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Abstract

Do neighbors influence job search behavior? We address this question using a Manski-type model with four search channels. Results show that neighbors' use of a channel affects individuals' own use, particularly for signaling one's job search in the media and using personal or professional networks, as opposed to more conventional methods such as contacting employers or intermediaries. We also find effects of neighbors' occupations. Our findings suggest that local social interactions may amplify labor market inequalities across neighborhoods, as there are stronger incentives to search when unemployed neighbors are actively searching and employed neighbors hold higher-status jobs.

JEL classification: J21, J64, R23.

Keywords: Job search, Neighborhood effects, Unemployment, Reflection issue, Location endogeneity.

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1 Introduction

Job search is a key determinant of matching outcomes in the literature on labor economics, featuring prominently in both theoretical search and matching models (Pissarides, 2000) and in empirical studies (Addison and Portugal, 2002; Schmutte, 2015). In the literature on neighborhood effects, one consistent finding stands out: local networks strongly influence job recruitment (Bayer et al., 2008; Hellerstein et al., 2011). It is therefore surprising that we know little about how social contacts within residential neighborhoods influence job search behavior.

This paper estimates the causal effects of neighbors' characteristics and behaviors on job search. Using a unique database with detailed information on job search actions, we estimate how close neighbors influence the channels used by unemployed individuals to look for work. We formalize these interactions in a canonical model *à la* Manski, distinguishing between endogenous and contextual effects — the influence of peers' behavior and peers' characteristics, respectively. This distinction matters, as each type of effect calls for different policy responses. We also add the influence of non-unemployed neighbors through their connection to the labor market and the quality of this connection. To address location endogeneity, i.e. the correlation of unobservables within neighborhoods due to sorting or common shocks, we include fixed effects at a broader neighborhood level, following Bayer et al. (2008), and we deal with the reflection issue, i.e. the impossibility of separately identifying endogenous and contextual effects in standard linear-in-means models, using the identification strategy proposed by Lee (2007) and developed by Boucher et al. (2014). We measure job search behavior by grouping detailed types of actions into four channels and estimate the model for each channel and for total search activity. Several robustness checks support our identification strategy: we test for the remaining within-neighborhood correlation based on observables, and we also use a network formation model to control for unobservables influencing sorting. We also exclude neighborhoods with public housing or restrict the sample to more comparable ones. Finally, we test for heterogeneous effects across building density and time.

Our results show robust endogenous effects across all channels and for total search activity. The two most common channels are direct contacts with potential employers and the use of personal or professional networks. Both exhibit endogenous effects, though smaller for direct contacts (a one-standard-deviation-increase in neighbors' use raises individual use by 5.0% relative to the mean) than for network-based search (6.5%). Endogenous effects for contacting employment intermediaries are slightly lower (4.6%). While the precise mechanisms remain uncertain, the stronger peer influence on network-based search and weaker effects for intermediaries suggest the role of information exchange: contacting intermediaries is well known, whereas learning who can help through networks may depend on neighbors. We also find influences from employed neighbors: a one-standard-deviation increase in the share of low-level occupations reduces direct search by 1.8%, search through signaling by 2.8%, and total search by 1.3%. These patterns align with individual-level determinants, where lower labor-market positions favor intermediaries, while higher-skilled individuals rely more on direct contacts, networks, and signaling. Although modest in magnitude, these effects are comparable to those of key individual characteristics such as gender or moving from low- to medium-skilled occupations.

Our paper contributes to three strands of the literature. First, we contribute to the literature on job search behavior. A large body of research shows substantial heterogeneity in how individuals search for jobs and how these strategies affect outcomes. Early studies emphasize differences in the effectiveness and costs of various search channels, including direct applications, public employment services, and informal referrals (Holzer, 1988; Addison and Portugal, 2002; Böheim and Taylor, 2001). Search strategies also reflect expectations: individuals adjust effort based on labor market conditions, job-finding costs, and anticipated job quality (Merlino, 2014; Stupnytska and Zaharieva, 2015; Beam, 2021). Evidence on individual determinants is mixed: less-privileged workers often rely on informal channels (Ioannides and Loury, 2004; Vázquez-Grenno, 2018), while highly educated individuals tend to mobilize networks more effectively (Bachmann and Baumgarten, 2013; Piercy and Lee, 2019). Social ties play a central role in job search and matching (Cingano and Rosolia, 2012; Zenou, 2015; Jackson et al., 2020), and affect job quality (Caliendo et al., 2015). Location also matters: search intensity declines with distance to city centers (Patacchini and Zenou, 2005), and local labor market conditions and living costs shape search behavior (Patacchini and Zenou, 2006). Nicodemo and García (2015) consider peer effects in job search, relying on sectoral variation in the use of network vs. non-network search methods, and show in the case of Colombia that the search channel used to find a job is influenced by the choices of employed neighbors' and how they found employment. We add to this literature by estimating neighborhood effects in the use of four different search channels, disentangling the impact of neighbors' characteristics and behaviors.

Second, we contribute to the literature on local peer effects in labor market outcomes. Following Wilson (1987), numerous studies show that living in disadvantaged areas reduces employment chances and that local employment shocks affect individual job prospects (Topa, 2001; Andersson, 2004; Jahn and Neugart, 2020; Eilers et al., 2021). Quasi-experimental evidence suggests, however, that proximity to employed neighbors provides limited benefits for adults once selection is accounted for (Chyn and Katz, 2021). Evidence on immigrants points to specific peer influences: employment outcomes are worse in immigrant-dense neighborhoods, driven largely by migrants' characteristics (Damm, 2014; Boeri et al., 2015). Other studies emphasize the role of local networks: residents of the same city block are more likely to work in the same block or same firm (Bayer et al., 2008; Hellerstein et al., 2011). Using French data, Hémet and Malgouyres (2019) confirm the role of neighborhood referral networks in unemployment exits, and further evidence suggests local ties affect job stability and wages (Hellerstein et al., 2014; Schmutte, 2015). Sociological studies also highlight the persistence and intensity of neighborhood ties, particularly at the building level, in facilitating job-related information exchange (Bonneval, 2021; Authier and Cayouette-Remblière, 2021). We extend this literature by showing that local networks influence not only employment outcomes but also job search behavior, through both endogenous effects — possibly due to imitation, social norms, and shared costs — and effects related to the job quality of employed neighbors.

Finally, we contribute to the literature on identifying neighborhood or place effects. Much of this literature examines how neighborhood composition — measured by poverty, unemployment, or average education — affects individual outcomes using reduced-form regressions, fixed effects, or quasi-experimental designs (see Galster, 2024). To our knowledge, no study separately identifies the effects of neighbors' composition and behavior, except

Wydick et al. (2011), who estimate peer effects at neighborhood, church, and village levels on a small sample of rural households using a binary choice model. Our paper leverages a unique French dataset, controls for location endogeneity with large neighborhood fixed effects, and employs a modern estimation approach to identify both endogenous and contextual effects at a fine-grained neighborhood scale.

2 Data and descriptive statistics

In this section, we first present the data used, define the estimation sample, and expose some individual-level descriptive statistics. We then describe our measures of job search behaviors.

2.1 Data and estimation sample

This paper relies on data from the French Labor Force Survey over the period 2014 to 2019. The FLFS is since 1950 a unique source for describing the state and evolution of the labor market in France. It provides a detailed description of households, including, for each member over the age of 15, their situation in the labor market, the characteristics of their main job, and their level of education, with a certain time dimension. Each quarter, the sample comprises about 67,000 dwellings and 108,000 individuals. The FLFS is a panel of dwellings, each surveyed for a period of six consecutive quarters. In each wave, the sample is based on 2,500 geographical sectors, each containing about 120 dwellings. Each sector is divided into six clusters of about 20 contiguous dwellings. When a sector enters the sample, one of its clusters is surveyed for a period of six quarters, before being replaced by a second cluster for the next six quarters. This procedure is carried on until all six clusters of the sector have been surveyed, after 36 months, at which point the sector is replaced by a new one.

Consisting of about 20 dwellings, FLFS clusters provide a precise definition of a local neighborhood. In urban areas, a cluster very often corresponds to the different dwellings of an entire building or to some floors of that building. Even in low urbanized areas, all the dwellings in a cluster might be located at the intersection of two streets and constitute therefore a very small neighborhood.[1] Consequently, individuals surveyed in the same cluster and quarter can be considered as close neighbors who can interact on a daily basis. We thus define the individual's reference group as her neighbors in the cluster in the same quarter. We should speak of *cluster* $\times$ *quarter group*, but for conciseness will simply write *cluster* in the following when there is no risk of confusion. The aggregation of clusters into sectors provides two nested levels of neighborhoods. Observing individuals living in very close clusters within the same sector is a key to identifying neighborhood effects in our analysis, as will be explained in Section 4. Note that since clusters within a sector are included in the FLFS sample sequentially, individuals in different clusters are not surveyed at the same time.

[1] The INSEE cluster construction rule requires that all dwellings belonging to the same floor be included in the same cluster. Figure A.1 in Appendix shows a cluster of 28 dwellings, all in the same building in Paris. Figure A.2 presents the example of a cluster of 23 dwellings in a rural community.

When building the sample, we decide to focus on large urban areas in mainland France.[2] As we observe very little on-the-job search in our data, we restrict the analysis of job search behaviors to unemployed individuals, aged between 15 and 64. The FLFS considers as unemployed, persons of working age (15 or over) who meet three conditions simultaneously: (i) being without employment during a reference week; (ii) being available to take up employment within two weeks; (iii) having actively looked for a job in the previous month or having found a job starting within the next three months. We remove unemployed individuals who have already found a job starting later, or who are seasonal workers observed in a dead period. If multiple unemployed are observed within the same dwelling at the same quarter, only one is randomly chosen, as we do not want to confuse neighborhood effects with interactions within households. We drop 195 individuals who are the only unemployed individual in a sector for identification issue, as well as one individual alone in her cluster. This selection results in a first full sample of 38,023 individuals, each of whom is observed to be unemployed in at least one quarter, for a total of 74,151 observations.[3]

As exposed in detail in Section 3, our identification strategy relies on comparing cluster (small neighborhoods) within sectors (large neighborhoods), assuming the randomness of allocation of individuals within sectors, which implies the absence of correlation between the individual's unobservables and that of her within-cluster neighbors. Each cluster can be observed more than once in our sample if it contains unemployed individuals in different quarters. The full sample indeed comprises 38,613 clusters $\times$ quarter and 10,684 clusters. The same unemployed individuals can be observed several times, which does not raise any concerns regarding identification. However, if a pair of unemployed individuals is seen twice in a cluster in different quarters, this may violate the random allocation hypothesis. Indeed, the individual's neighbors in the second observation of the pair is not a random draw of the potential neighbors in the sector, especially if there are some unobservables resulting in these two individuals being both unemployed twice. This is likely to generate some correlation between the individual's unobservables and that of her neighbors. To ensure that this correlation does not bias the estimates, we remove the repetitions over time of pairs of unemployed individuals. The procedure starts by counting the number of common pairs of unemployed between the different quarterly observations of each cluster. It then removes one of the two cluster $\times$ quarters with common pairs, starting with the cluster $\times$ quarters with the highest number of common pairs and randomizing when necessary, and iterates until no repetition of pairs is found between the different quarterly observations of a cluster. We remove cluster $\times$ quarters and not simply pairs of individuals in order not to break up the set of neighbors. Implementing this procedure removes one third of the observations in the full sample, one fifth of the cluster $\times$ quarters, and no sector.

The final estimation sample consists of 49,696 observations, 33,735 individuals, 10,684 clusters, 31,346 clusters x quarters, and 2,882 sectors. Since our sample covers a period of

[2] According to the 2010 INSEE zoning of urban areas, a "*large urban area*" is a group of touching municipalities encompassing an urban centre providing at least 10,000 jobs, and suburban districts in which at least 40% of the employed resident population works in the urban centre or in the municipalities attracted by this centre.

[3] We could have used the FLFS as a panel of individuals and identified social interaction effects based on their variability across quarters within individuals. However, only 57% of the unemployed in the sample are observed unemployed more than once.

twenty-four quarters, we can observe a maximum of four clusters in the same sector. As shown in Figure J.1 in the online Appendix, about half of the sectors in the estimation sample have three clusters, a quarter have four clusters, while the others have two clusters and a few have only one cluster.

Table B.1 and Table B.2 in Appendix present respectively the variable definitions for individual characteristics, and descriptive statistics on both the estimation sample, and the initial full sample including repeated pairs for comparison purpose. The estimation sample is representative of the unemployed in large urban areas in France. There is a very high proportion of young people: 38.9% are aged between 15 and 29. Consistently, the sample includes 17.0% of new entrants to the labor market, i.e. who have never worked before. 14.3% of the sampled unemployed were previously in middle occupations, 7.2% in high occupations (senior managers and higher intellectual occupations), while the majority were in low-level occupations (either blue-collar workers or low-level white-collar workers) before losing their jobs. Half of individuals hold low-level diplomas (vocational diploma or below). In terms of urban fabric, 40.7% of the individuals live in multifamily buildings in cities, among which 16.1% in high-rise housing projects usually more present in deprived neighborhoods. More than a third live in houses.

2.2 Main measures of job search behavior

The literature typically defines job search behaviors in terms of intensity (the number of actions and time dedicated) and job search channel (the type of actions taken). Our focus will be on the channel. The FLFS includes twenty-one questions regarding the job search activities of individuals during a reference week. For example, respondents are asked if they replied to a job advertisement, or contacted the national employment agency, an interim firm or a placement operator. These questions allow us to identify the specific types of actions individuals took. However, we do not know how many actions were taken in each category, nor how much time was spent on each of the actions. This motivates our choice to focus on job search channels.

We first select nine questions, dropping those with low positive answers rates (e.g., attending a job fair or job forum), as well as those which are more likely to be consequences of previous job search actions (e.g., having had an interview for a job).[4] The list of these nine questions along with the share of positive answers are presented in Figure D.1 in the online Appendix.[5] We consolidate these questions into a smaller number of channels based on a factorial analysis of co-occurences among individuals.[6]
The resulting clustering of job search actions is summarized in Table 1, in decreasing order the four factors' contributions to the variance in the factorial analysis. These groups of

[4]The list of excluded questions is in Table D.2 in the online Appendix.

[5]A measurement error could come from individuals getting fed up with the questionnaire and answer "no" to all the last job search related questions. We checked that the probability of answering "no" to a job search question is not related to its order of appearance in the survey.

[6]Specifically, we first compute tetrachoric correlations between the positive responses to each of the questions. The correlations are presented in Table D.1 in the online Appendix. We then run a factor analysis on the correlation matrix allowing for four factors. Each question is associated with the factor on which it has the highest loading, and questions associated with the same factor are grouped together. In order to be as general as possible, this analysis is performed on an enlarged sample of 80,038 observations including all unemployment periods observed in FLFS 2014-2019, in large urban areas for individuals aged 15-64. A hierarchical clustering produces the same grouping of questions.

actions have meaningful interpretations in terms of job search channels. The three questions with the highest load on the first factor correspond to direct contacts with potential employers. The two questions grouped on the second factor correspond to using personal and professional networks. The two questions loaded on the third factor correspond to signaling in a media that one is searching for a job. Lastly, two questions grouped on the fourth factor represent contact with institutional job placement intermediaries. In the following, we will use the terms *Direct contacts* for the first channel, *Networks* for the second, *Signal* for the third, and *Intermediaries* for the fourth channel.[7]

For each of these four channels, we define the measure of use simply as the sum of positive responses to the questions part of the group. The variables *Networks*, *Signal* and *Intermediaries* can thus take values 0, 1 or 2, the variable *Direct contacts* values between 0 and 3. Finally, we define a global job search variable, ranging between 0 and 9, which simply sums positive responses to the nine questions considered and thus constitutes a measure of the diversity of means used to search for a job. We call it simply *Total* in short in the following.[8]

Distribution of job search variables. Table 2 presents the distribution of the five job search variables in the estimation sample. Rescaled by their respective ranges, the most frequently used channel is direct contacts with employers, with a mean of 1.50 out of a maximum of 3 and used by three-quarters of the population. Specifically, 28.1% of individuals use two different methods of direct contact, 23.4% use all three, and 23.6% use only one. The next most common channel is search through networks, with a mean of 0.95 out of 2, used by about two-thirds of the sample. Among individuals using networks, a bit more than half rely on either personal or professional contacts, while the others use both types. Contacts with intermediaries rank third. In this category, three quarters of respondents contact only one type of intermediary, whereas one quarter contact both. Signaling one's job search is the least used channel, with 60.5% of individuals not using it at all. The total search variable has a mean of 3.66 and is relatively well distributed. Specifically, 11.8% of individuals engage in only one type of action, 32.9% engage in two or three types, 31.1% engage in four or five types, 19.8% take six or more actions, and fewer than 1% respond positively to all nine questions.

2.3 Alternative measures of job search behavior

In addition to the main measures based on the factorial analysis, we construct an alternative, item-anchored index following Cunha et al. (2010). This approach exploits the relationship between the nine basic job search actions and the probability of finding a job. Specifically, we estimate a linear probability model of being unemployed at quarter t and employed at quarter $t+1$, as a function of job search behavior at t, including indi-

[7]We hypothesize that unemployed individuals imitate the job search behaviors of their neighbors, but the *Networks* variable is not to be confused with contacts with neighbors. It includes contacts with family, friends and professional connections inside and outside the neighborhood. It is also important to note that the term *networks* does not refer to the analysis of social interactions on a network.

[8]Individuals may develop their search effort combining or not different channels. The correlations between the four variables show that only little correlation remains between them, as a result of the factorial analysis used to define the four channels.

Table 1: The nine job search actions and their clustering into four channels

Direct contacts with potential employers - *Direct contacts*
- Have you made a direct approach to an employer by personally submitting an unsolicited application in the company or at a trade fair or job forum?
- Have you made a direct approach to an employer by personally submitting an unsolicited application by postal mail, email, or on the firm website?
- Have you responded to a job offer?
Using personal and professional networks - *Networks*
- Have you turned to personal contacts such as family or friends to find a job or set up a business?
- Have you turned to professional contacts to find a job or set up a business?
Signaling that one is searching for a job - *Signal*
- Have you shared via digital social networks that you are looking for a job, and made your professional profile known?
- Have you had a job search advertisement placed or posted, in a newspaper or on internet?
Contact with institutional job placement intermediaries - *Intermediaries*
- Have you contacted one (or more) temporary employment agencies or a placement operator?
- Have you contacted the French National Employment Agency[(a)], the Agency for the Employment of Managers, a placement operator, the Chamber of Commerce and Industry or any other public institute?

Notes: (a) Excluding mandatory contacts with the French National Employment Agency not really devoted to searching for a job.
Source: INSEE, FLFS questionnaire.

Table 2: Distribution (in %) of the five job search measures in the estimation sample

Number of actions	0	1	2	3	4	5	6	7	8	9	Mean	SD
Direct	25.0	23.6	28.1	23.4							1.499	1.104
Networks	34.3	35.9	29.7								0.954	0.799
Signal	60.5	30.5	9.0								0.485	0.655
Intermediaries	42.4	42.8	14.8								0.724	0.705
Total	4.4	11.8	15.5	17.4	16.8	14.3	10.3	6.0	2.8	0.7	3.662	2.039
Observations						49,696						

Notes: 16.8 % of unemployed individuals in the sample use a total of four different types of actions. The 49,696 observations correspond to 33,735 individuals interviewed when unemployed in different FLFS waves.
Source: French Labor Force Survey, estimation sample as defined in the text.

vidual fixed effects to control for unobserved heterogeneity.[9] The estimated coefficients, presented in Figure E.1 in the online Appendix, are then used as weights in a weighted sum of the nine job search items. This procedure yields an alternative measure of total job search in which more weight is assigned to actions more strongly associated with subsequent employment. We apply the same method to the four job search channels, using the relevant subsets of items (see Table E.1 in the online Appendix for the full set of coefficients). These variables are referred to as *item-anchored measures* in what follows. Compared to a simple unweighted sum of positive responses, the item-anchored measure of total job search assigns greater weight to contacting temporary employment agencies, responding to job offers, and using personal contacts. These actions also receive higher weights within their respective channels.[10]

These item-anchored measures may be better suited to reveal peer effects. Peer influence is likely to be stronger for job search actions that are more effective in leading to employment. For instance, if contacting a temporary employment agency is particularly efficient, it may induce stronger imitation among neighbors. By giving greater weight to such actions, our item-anchored measures may thus capture stronger peer effects. A further advantage of these alternative measures is that the five variables now share a comparable scale, ranging between 0 and 1 (see their distributions in Figure E.2 in the online Appendix). Unsurprisingly, the correlations between the two sets of measures are very high—above 0.95 for all, reaching 0.99 for *direct contacts.*

2.4 Individual determinants of the use of job search channels.

We consider here the main measures of job search and briefly anticipate the main estimated model, which will be fully presented in Section 3, by commenting on the coefficients related to individual characteristics (see Table C.1 in the Appendix for the full set of estimates). This descriptive step is useful to illustrate how job search behaviors vary systematically across observable characteristics and to give some body to the different job search channels we defined.

Direct contacts with potential employers are more common among young unemployed individuals and those with a stronger labor market background, that is, those previously employed in high-level occupations. Women also appear more likely than men to engage in this type of search, while foreigners and parents use it less. Job search through networks shows a somewhat similar pattern: it is mainly used by unemployed individuals previously in high-level occupations, by those with an employed partner, and also by foreigners and men. Interestingly, having children increases the use of this channel, possibly because parenthood broadens social ties and facilitates access to wider networks. Making one's search visible through media is more frequent among younger individuals, unemployed with prior high-level occupations, women, and French citizens. By contrast, job search through institutional intermediaries is primarily used by individuals facing less

[9]We use the same sample as in the factorial analysis, with the addition of the employment periods of the sampled individuals. Since our goal is to obtain weights for constructing indexes of job search activities and not to perform causal inference, and because of left censoring, we do not estimate a duration model.

[10]Estimating neighborhood effects for each individual job search action would be of interest. However, our current estimation framework cannot handle binary outcomes, and econometric methods for identifying peer effects with binary dependent variables are still under development.

favorable labor market conditions. Those previously in low-level occupations, as well as younger and foreign individuals, are more likely to rely on this channel. Across all search methods, individuals who have never worked before consistently undertake fewer types of actions, underscoring the disadvantage of weak initial labor market attachment. Similarly, unemployed individuals with inactive partners also search less, which may reflect household resource dynamics or lower perceived returns to job search effort.

In summary, unemployed individuals previously in high-level occupations use a wider range of job search actions, except for contacts with institutional intermediaries. Younger individuals also display greater search intensity, including a higher use of contacts with intermediaries. By contrast, those previously in low-level occupations engage in fewer types of search actions, except that they rely more on institutional intermediaries. Unemployed individuals who have never worked before search less across all channels, and women also undertake fewer types of actions, except that they are more likely to contact potential employers directly.

When comparing our results to the existing literature, some divergences appear. Our findings on the use of networks do not fully align with those of Ioannides and Loury (2004) and Vázquez-Grenno (2018), who report that more educated individuals are less likely to rely on informal contacts. By contrast, our results are broadly consistent with Bachmann and Baumgarten (2013), who also find that individuals in higher occupational positions and those with an employed partner are more likely to rely on networks. Likewise, our evidence resonates with the typology put forward by Piercy and Lee (2019), in the sense that different search modes cluster around distinct socio-demographic groups (e.g., younger individuals relying more on signaling and direct search). Overall, despite some discrepancies with earlier studies, these patterns support the validity of our job search measures and underline how individual characteristics shape the use of specific job search channels.

3 Empirical strategy

We frame our research question within the broader context of research on peer effects. We aim to identify the impact on unemployed individuals' job search behaviors of unemployed neighbors' job search behaviors, unemployed neighbors' characteristics, and other neighbors' characteristics. As previously explained, the individuals who are considered as neighbors live in the same cluster as the individual, where interactions between neighbors are likely to take place.[11]

The influence of peers' job search behaviors on unemployed individuals' job search behaviors is called *endogenous effects* in Manski's terminology. Several mechanisms can explain the existence of these endogenous effects. First, psychological factors and social pressure, with the need to conform to the social norms promoted within the reference group, can be a cause of these imitative behaviors. If an unemployed individual lives in a neighborhood where being unemployed is frowned upon, and where her unemployed

[11] In addition to the within-neighborhood interactions we consider here, social interactions occur within other groups, such as those related to family or friendship networks. We focus here on neighborhood-related social interactions, which can in fact intersect with friendship relationships.

neighbors are actively looking for employment, she might face a cost of deviating from the group's social norm and feel social pressure to act similarly. Second, the similarity in behaviors can also occur through a word of mouth learning process. The more individuals of a group exert a certain behavior, the more the costs associated to this behavior are reduced for other members of the group. We can for instance imagine that unemployed neighbors who face the same situation would help each other through advice and tips regarding what they consider as the easiest or most efficient job search methods, which will therefore be associated to lower costs. This seems all the more true as Caliendo et al. (2015) show that beliefs about the efficiency of the job search method play an important role in job search, while Nicodemo and García (2015) show that the use of networks vs. non-networks job search methods is influenced by neighbors' choices.

We also examine how neighbors' characteristics influence job search behaviors. We first hypothesize that a low share of employed neighbors may reduce search intensity, as unemployed individuals may develop pessimistic expectations about their job prospects and feel less social pressure to search (Patacchini and Zenou, 2006). Beyond the psychological costs already associated with unemployment, such a context may lead unemployed individuals to feel that they do not stand out from others in their situation, resulting in discouragement and lower effort. Conversely, a higher share of employed neighbors may strengthen the social stigma attached to unemployment, while also improving access to job information and networks that facilitate search (Bayer et al., 2008; Hellerstein et al., 2011, 2014; Topa and Zenou, 2015). These benefits are likely stronger when employed neighbors hold high-level occupations, which can enhance the quality of information and increase opportunities for direct referrals to employers (Schmutte, 2015). Encounters or informal exchanges between employed and unemployed neighbors can make the latter's situation known, enabling advice or referrals through word of mouth. Finally, living near high-skilled workers may also expose unemployed individuals to a cultural environment more conducive to active job search, where role models and social norms reinforce the value of employment and the means to achieve it (Akerlof, 1980; Wilson, 1987).

Because they may rely on different mechanisms, but also for identification issues that we discuss below, these influences of neighbors' characteristics have to be considered separately for unemployed neighbors and for other neighbors. The impacts of unemployed neighbors characteristics are *contextual effects* in accordance to Manski's model, while the impacts of non-unemployed neighbors characteristics are called here *group effects*.[12] The variables capturing group effects reflect the three types of mechanisms reviewed above and consist in the shares of non-unemployed neighbors who are employed, and the shares of employed neighbors who are in high-level occupations, and in low-level occupations. The first variable reflects the probability of running into someone in the neighborhood who is employed and therefore connected to the job market. The other two variables reflect the probability to be in touch with individuals in positions that may or may not provide access to higher-quality information. We also want these variables to capture the quality of the environment as being or not conducive to job search.[13]

[12]As in practice there is very little job search by employed individual, the behavior of non-unemployed neighbors is not considered here.

[13]We decided to favor the use of occupations over diplomas to describe the labor market status, because they have the advantage of capturing the exact jobs done by workers and parts of the effects of past careers.

The choice of contextual variables is motivated by the economic mechanisms hypothesized above. We thus consider only the level of the previous occupation, that is, a subset of the characteristics included as individual determinants of job search. Given the nearly zero share of high-level occupations among unemployed neighbors in our sample (see Figure G.1, in the online Appendix), we include only on the share of neighbors in ex-low-level occupations or those who have never worked.

In the following, we first present the empirical model and develop our identification strategy with regard to reflection and location endogeneity.

3.1 Empirical model

We estimate a linear-in-means model which writes as follows:

$$\begin{aligned} Y_{igst} = \alpha + \lambda\ \overline{Y}_{gst\backslash i} + \beta\ \mathbb{1}_{n_{u_i gst}>0} + \sum_{j=1}^{J} \gamma_j\ \overline{Z}_{jgst\backslash i} \\ + \sum_{k=1}^{K} \delta_k\ \overline{W}_{kgst} + \sum_{l=1}^{L} \rho_l X_{ligs} + \theta_t + \eta_{s_g} + \epsilon_{igst} \end{aligned} \tag{1}$$

where

- Y_{igst} is the job search of unemployed individual i in cluster g in sector s at quarter t; search through direct contacts with employers, through networks, through signals, through intermediaries, and total search are considered in turn in separate estimations;

- $\overline{Y}_{gst\backslash i} = \frac{\sum_{u_i \in gst} y_{u_i}}{n_{u_i gst}}$ is the endogenous effect, that is the average job search behavior of i's unemployed neighbors for the same channel as Y_{igst}, with $n_{u_i gst}$ their number; individual i is excluded as part of the identification strategy (see next subsection) and individuals belonging to her household are excluded so as to avoid a source of endogeneity;

- $\mathbb{1}_{n_{u_i gst}>0}$ is a dummy variable that takes the value 1 if i has at least one unemployed neighbor at quarter t; β aims at capturing the unobserved characteristics of isolated unemployed for whom the endogenous and contextual effects are null; it may also account for the impact of the perception of the unemployment status in the neighborhood.

- $\overline{Z}_{jgst\backslash i} = \frac{\sum_{u_i \in gst} Z_{ju_i}}{n_{u_i gst}}$ are $J = 2$ variables for contextual effects, namely the share of low-level previous occupations and the share of individuals having never worked among i's unemployed neighbors; individual i and individuals belonging to her household are excluded;

- $\overline{W}_{kgst} = \frac{\sum_{a_i \in gst} W_{ka_i}}{n_{a_i gst}}$ or $\frac{\sum_{e_i \in gst} W_{ke_i}}{n_{e_i gst}}$ are $K = 3$ variables for group effects: the share of employed among i's non-unemployed neighbors, with $n_{a_i gst}$ their number, the share of high-level, and the share of low-level occupations among i's employed neighbors, with $n_{e_i gst}$ their number; individuals belonging to individual's i household are excluded;

- X_{ligs} are L individual characteristics likely to affect the different dimensions of job search; they control for observed heterogeneity and include: age, sex, previous occupation, nationality, having or not a child, and the partner's employment status;

- θ_t are quarter time dummies to control for common time trends;

- η_{s_g} are sector fixed effects that capture observed and unobserved characteristics that impact job search intensity and are common to all individuals living in the same sector; they help us to deal with location endogeneity.[14]

Table 3 presents the definition of the main explanatory variables in Equation 1 and some variants used in the robustness checks. Table B.1 in the Appendix defines control variables. Figure G.1 in the online Appendix shows the distributions of the number of neighbors used to compute the endogenous, contextual and group effects, and how these neighbors are distributed in terms of characteristics in the estimation sample.

3.2 Identification strategy

Two identification issues must be carefully addressed to consistently estimate neighborhood effects. The first concerns location endogeneity, which generates *correlated effects* in Manski's terminology. These correlated effects arise from two sources. First, due to sorting in the housing market, individuals with similar observed and unobserved characteristics tend to reside in the same neighborhood. This non-random sorting can be reinforced by the very existence of neighborhood effects, as individuals may choose a location based on anticipated local social interactions. Second, there are random shocks common to all individuals in a neighborhood. Consequently, residents of the same neighborhood share unobservables, and failing to control for them would bias estimates of neighborhood effects.

To address this location endogeneity, we adopt a strategy first proposed by Bayer et al. (2008) and used more recently by Grinblatt et al. (2008), Schmutte (2015), Solignac and Tô (2018), and, with the FLFS data, by Hémet and Malgouyres (2018). The approach relies on two nested levels of neighborhoods: a lower level where social interactions are assumed to occur, and a higher level for which fixed effects are included to control for location choice. In our application, we include sector fixed effects, so that neighborhood effects are identified based on variation across clusters within sectors. The key identifying assumption is that, while households may choose a large neighborhood, they cannot select a specific cluster within it. Clusters can be thought of as, for example, different floors in a multi-family building or a specific block within a larger neighborhood. A household's choice of a particular cluster is constrained by the available housing units at the time of relocation, and therefore close to random. If this assumption holds, unobservables affecting an individual's job search behavior are uncorrelated with those affecting her neighbors, so that any observed impact of neighbors' behavior can be interpreted as causal. We provide robustness checks supporting this identifying assumption in Section 5.

[14] We decided not to include fixed effects at the reference group level, although Lee (2007)'s identification strategy, as shown in Boucher et al. (2014), allows it, because the small number of unemployed individuals in the clusters calls into question the proper estimation of the corresponding fixed effects.

Table 3: Variable definition - Job search behavior and social interactions

Variables	Definition
Explained variables	
Direct	Number of times an individual answered "yes" to the three FLFS questions regarding direct contacts with potential employers, i.e. face-to-face, or online unsolicited application, and responding to job advertisements.
Networks	Number of times an individual answered "yes" to the two FLFS questions regarding the use of personal or professional connections to find a job.
Signals	Number of times an individual answered "yes" to the two FLFS questions related to signaling one's will to find a job, i.e. the use of digital media to find a job, and posting job advertisements.
Intermediaries	Number of times an individual answered "yes" to the wo FLFS questions regarding contacts with institutional employment organizations, i.e. the French National Employment Agency, and temporary employment agencies.
Total	Sum of the four previously defined variables.
Endogenous effects	
Unemp. neighbors' mean behavior	Average search intensity of unemployed neighbors in the cluster, individual i and her household members excluded, for each of the four job search channels (direct, networks, signals, intermediaries) or total search.
Contextual effects	
% ex-low-level occupations	Share of ex low-level occupations among unemployed neighbors in the cluster, individual i and her household members excluded.
% has never worked	Share of unemployed neighbors who have never worked in the cluster, individual i and her household members excluded.
Group effects	
% employed	Share of employed neighbors in the cluster, individual i's household members excluded.
% high-level occupations	Share of high-level occupations among employed neighbors in the cluster, individual i's household members excluded.
% low-level occupations	Share of low-level occupations among employed neighbors in the cluster, individual i's household members excluded.
Has unemployed neighbors	1 if individual i has at least one unemp. neighbor / 0 if she has none.

Notes: This table presents the definition of the variables of interest included in Equation 1.

A subtler identification issue arises in linear-in-means social interaction models, where social groups form a partition of the population, and individuals are influenced by all members of their group but by no one outside it. As Manski (1993) demonstrated, in this setting the mean outcome of the group (the endogenous effect) is perfectly collinear with the mean characteristics of the group (the contextual effects). This problem is commonly referred to as the reflection issue. We address the reflection issue following Lee (2007) and the development by Boucher et al. (2014). The strategy builds on Moffitt (2001)'s observation that, although all individuals in a group share the same peers in Manski's model, exclusive averaging — excluding the individual when computing her peers' mean — ensures that each individual effectively has her own group of peers. As Lee (2007) shows, this approach resolves the reflection problem when groups differ in size.[15] More-

[15]See Bramoullé et al. (2009) for a formal presentation of these arguments.

over, Boucher et al. (2014) show that identification is stronger when group sizes are small and heterogeneous. Our estimation sample meets these conditions: it contains 31,346 clusters, with an average of 1.58 unemployed individuals per cluster, a standard deviation of 0.93, and a maximum of 11 (see Table J.1 and Figure G.1 in the online Appendix).

This identification strategy can be implemented with an instrumental variable method or a conditional maximum likelihood estimator (Lee, 2007). As shown in Boucher et al. (2014), the IV method is based on the fact that within each group, each individual has a specific group of peers thanks to exclusive averaging, so that the aggregate characteristics of individual-specific group of peers can be used as instruments. The maximum likelihood method leverages the fact that positive peer effects reduce the dispersion in outcomes within groups, and the intensity of the negative correlation is higher in smaller groups. The dispersion of group sizes thus gives an exogenous variation in coefficients that allows to identify the effects. Moreover, the shape of the reduction is different for contextual and endogenous effects, which allows to estimate them separately. Monte-Carlo studies confirm that the ML method provides more precise estimations as compared to IV (Boucher et al., 2014). The model has the same form as a spatial autoregressive model in which each individual is influenced by his neighbors (Lee, 2007). The model can therefore be estimated using a conditional quasi-maximum likelihood estimator developed for SAR models, as suggested by Lee (2004). This is the estimator we use here.[16]

Finally, note that we consider that the explained variables in our analysis are not discrete choice variables but rather, as in Davezies et al. (2009), continuous variables, that is, for each job search channel, how many different methods an individual uses to find a job, observed as a discrete variable, namely how many times the individual answered yes to a set of questions related to this channel.[17]

4 Results

4.1 Main results

Table 4 presents the estimated coefficients for the variables of interest of Equation 1, while Table C.1 in the Appendix presents those of the control variables, that we have already commented on in Section 2.4.

Endogenous effects. Table 4 points to the presence of positive and highly significant endogenous effects for each of the four job search channels and for total search activities. We observe that the more the unemployed neighbors engage in a type of action, the more individuals do so. The highest estimated coefficients of endogenous effects are for search through signals, which is however the least used channel. A one-standard-deviation increase in the neighbors' average use of signals fosters the use of this channel by 0.046 units, that is, 9,5% relative to the mean. To illustrate the intensity of this effect, it is

[16]We use the SAR function of the R package CDatanet written by Aristide Houndetoungan; see `https://cran.r-project.org/package=CDatanet`.

[17]In doing so, we favor the use of the identification strategy developed by Lee (2007) over the use of non-linearity as an identification strategy. An early attempt at developing count data models with peer effects is proposed by Houndetoungan (2024). We do not use this approach, as it does not allow for the inclusion of fixed effects which is an essential component of our strategy.

comparable to the increase produced by changing from foreign origin to being of French citizenship. More interestingly, a one-standard-deviation increase in the neighbors' average use of search through networks raises the use of this channel by 0.062 units, that is, 6,5% of the mean. This increase is similar to the one produced by being male rather than female. Search through networks is thus one of the two most used channels, and is also affected by large endogenous effects. Direct contacts with potential employers is largely used, but does not exhibit endogenous effects as large as search through networks. The impact of a one-standard deviation in the corresponding neighbors' average is 0.075 units, that is, 5,0% of mean, which is similar to being female rather than male. Search through intermediaries exhibits more moderate endogenous effects. The impact of a one-standard deviation in the corresponding neighbors' average is 0.033 units, that is, 4,6% relative to the mean, the same positive impact as changing from intermediary occupations to low-level occupations. Finally, endogenous effects on total search activities are the result of these different impacts. The impact of a one-standard-deviation increase in average neighbors' total search is 0.177 units, that is, 4,8% relative to the mean.

We hypothesized two different mechanisms underlying endogenous effects in job search. Unemployed individuals might increase job search activities due to social pressure to act similarly as their peers and to conform to the social norms promoted within the neighborhood, known as a place of socialisation, or be discouraged by others (*"You will not find a job. The economic situation is bad"*). Or, they may adopt imitative behaviors due to the lower costs of acting like their peers, thanks to the exchange of information between unemployed neighbors who would advise each other regarding the right channel to use. Our results tend to favor the second hypothesis. Indeed, social pressure or conformity should impact the different channels similarly, as any mean would be considered as valuable. On the contrary, the higher impact of endogenous effects on search through networks and the lower impact on search through intermediaries might signal the impact of information exchange. Contacting employment intermediairies is a well-known way to search for a job, whereas information on who is able to help in searching for a job might require to be informed by neighbors. Distinguishing between the two kinds of hypotheses is beyond the scope of this analysis, and the differences in estimated impacts are small, but these results might be a first step in this direction.

Contextual effects. The estimated coefficients for the two variables describing the unemployed neighbors' characteristics suggest that contextual effects are not the primary drivers of job search behaviors. Intuitively, this is not surprising, as unemployed neighbors, currently not connected to the labor market, are less likely to be helpful in job search. Their characteristics are not as important as their search activities. That said, we do find a slightly significant (at the 10% level) and positive impact of the share of unemployed individuals who have never worked on total search, driven mainly by search through direct contacts with potential employers. This result suggests that environments composed of newcomers to the labor market, and possibly younger individuals, may encourage the use of direct approaches, such as unsolicited applications.

Table 4: Main regression results

	Explained variable				
	Total	Direct	Networks	Signal	Intermed.
	(1)	(2)	(3)	(4)	(5)
Endogenous effects					
Un. neighbors' average intensity	0.079***	0.072***	0.086***	0.091***	0.056***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	−0.018	−0.026	−0.002	0.011	0.003
	(0.033)	(0.018)	(0.013)	(0.010)	(0.011)
% has never worked	0.080*	0.050**	0.008	0.016	0.009
	(0.044)	(0.024)	(0.017)	(0.014)	(0.015)
Has unemp. neighbor (0/1)	−0.309***	−0.106***	−0.073***	−0.063***	−0.057***
	(0.031)	(0.017)	(0.009)	(0.009)	(0.010)
Group effects *(among non-unemp. neighb.)*					
% employed	0.014	0.043	0.021	−0.028	−0.023
	(0.078)	(0.044)	(0.031)	(0.025)	(0.027)
% low-level occupations	−0.190**	−0.110***	−0.042	−0.055***	0.018
	(0.067)	(0.036)	(0.025)	(0.021)	(0.023)
% high-level occupations	0.0008	−0.089*	0.084**	0.050*	−0.046
	(0.092)	(0.056)	(0.036)	(0.029)	(0.033)
Indiv. characteristics	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-96,644	-68,816	-52,423	−43,318	-48,132
N (Obs./ Sectors/ Clusters x t/ Indiv.)	49,696 / 2,882 / 31,346 / 33,735				
Dependent variable mean	3.66	1.50	0.95	0.49	0.72
Dependent variable s.d.	2.04	1.10	0.80	0.66	0.71

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents the estimated coefficients for the variables of interest in Equation 1, estimated on the main estimation sample. See Table B.1 and Table 3 for a detailed presentation of the independent variables and Table C.1 for the full set of estimated coefficients.

Having unemployed neigbors. The endogenous and contextual effects are null if the individual has no unemployed neighbors. The dummy variable *Has unemployed neighbors* thus aims at capturing the effect of being or not an isolated unemployed. For the five search variables, we observe a negative impact of having unemployed neighbors. This impact is consistent with the idea that having at least one unemployed neighbor lessens the social pressure of remaining unemployed and decreases job search activities. This negative effect combines with the search activities of the unemployed individuals and the impacts of their characteristics, so that the global impact of having unemployed neighbors actively searching for a job might result in stronger job search.

Group effects. Group effects capture the impact of the connection to the labor market of the neighbors. Although we do not find any impact of the share of employed neighbors, the occupation of employed neighbors, which reflects their position in the labor market, matters. The share of low-level occupations in the neighborhood negatively affects all types of job search except contacts with intermediaries, although some effects are not statistically significant. This result is consistent with the patterns observed for individual determinants of search and the idea that contacts with intermediaries are favored by individuals with low labor market positions, while direct contacts with employers, the use of networks, and signaling are associated with higher-level occupations. A one-standard-deviation increase in the share of low-level occupations in the neighborhood (+24.7%), which roughly corresponds to moving from the 5th to the 8th decile of the distribution, that is, a sizeable change in the composition of the neighbors, decreases direct search by 0,027 units (1.8% relative to the sample mean), job search through signals by 0,014 units (2.8%), and total search by 0,047 units (1.3%). The negative impact on direct contacts with employers and signaling might be interpreted as individuals lacking the knowledge or confidence to contact employers directly or signal their job search because their neighbors do not have good connections to the labor market.

We also find that a higher share of neighbors in high-level occupations fosters search through networks, with a one-standard-deviation increase (+18.2%, equivalent to moving from the 5th to the 8th decile) producing an increase by 0,015 units (1.6% with respect to mean intensity) in this channel. Although the networks considered here are not limited to the neighborhood, one of the possible networks unemployed can call upon are those neighbors in high-level occupations who could recommend them to one of their acquaintances, or own information of quality on job opportunities. On the contrary, direct contacts with employers are slightly negatively affected by a high share of high-level occupations, possibly due to a perceived competition with others for referrals in these areas. Finally, we observe non-significant group effects for job search through intermediaries, which is not surprising as this behavior corresponds to a more basic way of finding a job, where the characteristics of neighbors are not likely to play a role.

4.2 Results with alternative measures of job search behavior

Table 5 presents the estimated neighborhood effects for the item-anchored job search variables. We are interested in the direction of the changes in the neighborhood effects, especially for total search activities, for which the item-anchored measure gives more weight to contact with temporary employment agencies, responses to job advertisements, and the use of personal connections.

Overall, the endogenous effects are weaker with the item-anchored measures than with the unweighted measures, though none of the differences is significant (see Figure 1 for a comparison of the endogenous effects using the main and the item-anchored measures).[18] A one-standard-deviation increase in the neighbors' average behavior increases total search activities by 3.9% relative to mean search intensity, search through intermediaries by 3.7%, direct contacts with employers by 5.0%, search through networks by 5.3% and through signals by 5.2% (against 4.8%, 4.6%, 5.0%, 6.5% and 9.5% respectively for the main measure). Regarding contextual and group effects, we find only slight changes. The impacts of the share of unemployed neighbors who have never worked and of the share of high-occupations among employed neighbors are no longer significant. Thus, these measures, which give more weight to more efficient actions, do not provide evidence of stronger neighborhood effects. At the very least, these results suggest that peer effects do not promote the most effective job search methods, indicating potential inefficiency in the way social interactions influence job search.

[18] Given that the change in the unit of the measure affects both the dependent variable and the neighbors' average identically, we simply compare estimated coefficients of endogenous effects for the two measures. This comparison is not valid for the other estimated coefficients.

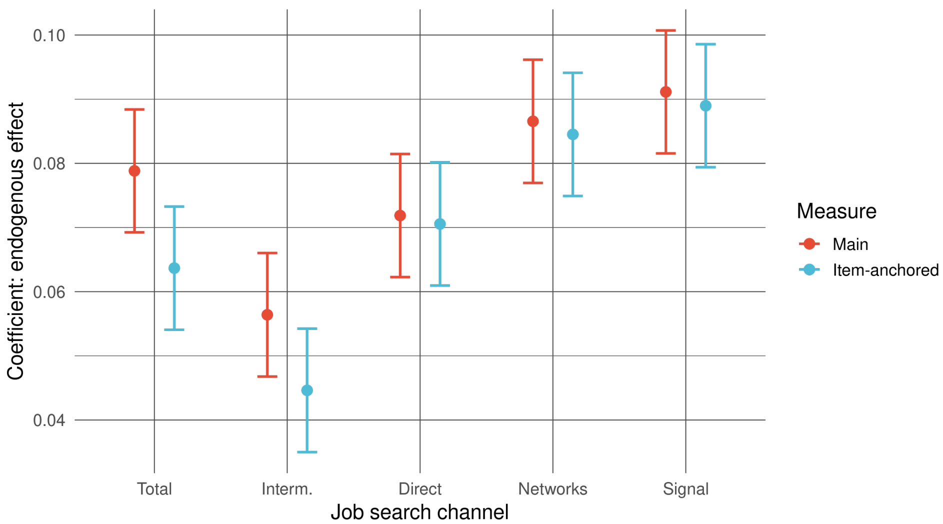
Table 5: Results with item-anchored job search measures

	Explained variable				
	Total (1)	Direct (3)	Network (4)	Signal (5)	Interm. (2)
Endogenous effects					
Un. neighbors' average intensity	0.064***	0.070***	0.084***	0.089***	0.045***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	-0.001	-0.002	-0.00007	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% has never worked	0.003	0.004**	0.0004	0.002	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Has unemp. neighbor (0/1)	-0.011***	-0.008***	-0.007***	-0.006***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Group effects *(among non-unemp. neighb.)*					
% employed	0.002	0.004	0.002	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
% low-level occupations	-0.006**	-0.008***	-0.004	-0.005***	0.002
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
% high-level occupations	-0.003	-0.007*	0.008**	0.005*	-0.007*
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Indiv. characteristics	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	50,029	60,847	65,620	64,583	53,230
N (Obs./ Sectors/ Clusters x t/ Indiv.)	49,696 / 2,882 / 31,346 / 33,735				
Dependant variable mean	0.158	0.090	0.061	0.063	0.081
Dependant variable s.d.	0.088	0.069	0.062	0.063	0.082

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents the estimated coefficients for the variables of interest in Equation 1, estimated on the main estimation sample, using the alternative measures of job search. See Table B.1 and Table 3 for a detailed presentation of the independent variables.

Figure 1: Estimated coefficients and 95% confidence intervals for endogenous effects for the main and item-anchored measures



4.3 Heterogenous effects depending on sector's built environment density

A question that naturally arises from the previous results is whether the neighborhood effects differ depending on population density, or by type of built environment, both of which can affect connections among neighbors. To address this question, we perform a heterogeneity analysis, estimating our main model separately on three samples, each representing sectors with a distinct range of built environment density. The FLFS describes dwelling surroundings according to five types of urban fabric, namely *scattered houses outside of urban agglomerations*, *houses in an (sub-)urban environment*, *flats in urban areas*, *flats in high-rise housing projects*, and *mixed housing*. We define a sector as dense if 80% of its dwellings are in surroundings consisting of flats in city blocks or in high-rise housing projects. A sector is considered non dense if more than 80% of its dwellings are in surroundings consisting of scattered houses or houses in an urban or suburban environment. The remaining sectors are defined as mixed, either because a large part of their dwellings are described as being in a mixed environment, or because they are a combination of houses and multifamily building environments.

Descriptive statistics in Table I.2 show that unemployed living in the dense sectors are for 70% of them in urban units above 200,000 inhabitants. About half of the sample in non-dense sectors are in rural municipalities or urban units less than 10,000 inhabitants, but one fourth of them are nonetheless in large cities. Individuals in the mixed sectors are in urban units of various sizes. As for individual characteristics, we do not observe striking differences between the three subsamples, except a significantly larger share of individuals of foreign citizenship or origin in dense sectors.

For conciseness, we present here only plots of the estimated coefficients for endogenous effects and two group effects, namely, the shares of low-level and high-level occupations among employed neighbors (Figures 2 and 3). Table F.2 in the online Appendix presents the full set of coefficients for the corresponding estimations. The estimated coefficients for endogenous effects differ across density subsamples. They are higher for dense sectors as compared to the others, with significant differences in estimated coefficients for search through networks and total search. A one-standard-deviation increase in neighbors' average increases search through personal and professional contacts by 0.088 units (8.8% with regard to sample mean) in dense sectors, as compared to 0.044 units (9.4%) in mixed sectors, and 0.044 units (8.8%) in non-dense sectors. The magnitude of the impact of neighbors behavior appears thus higher in dense environments, as compared to less dense built environments, although the differences in relative impacts are small due to a higher use of this type of search in dense environments. This stronger impact on search through networks and on the four other channels results in more striking differences in endogenous effects for total search. A one-standard-deviation increase in neighbors' average increases total search by 0.234 units (6.5% relative to mean search intensity) in dense sectors, as compared to 0.157 units (4.3%) in mixed sectors, and 0.143 units (3.9%) in non-dense sectors.

Regarding group and contextual effects, we first note that the estimated coefficients do not differ significantly across the three subsamples. The reduced size of these subsamples naturally leads to larger standard errors compared to the main results. However, two new significant coefficients emerge in dense sectors. First, a higher share of low-level occupations among employed neighbors negatively affects search through networks in dense environments. This finding mirrors the positive effect of high-level neighbors observed in the main results, suggesting that this type of search benefits from neighbors' labor market position — especially in dense areas. Second, the share of high-level occupations among employed neighbors significantly reduces search through intermediaries. This effect was not detectable in the full sample but aligns with the pattern that this channel is typically used by individuals with lower labor market positions. These new effects are noteworthy because dense sectors — concentrated in large urban units — appear to be the most homogeneous in terms of population composition.

Overall, these results suggest that job search behaviors are more impacted by neighborhood effects in dense environments, where social encounters are likely more frequent, than in other environments. This result is at odds with the common view that denser urban environments are synonymous with anonymity. Instead, it demonstrates that social ties are active in these neighborhoods and influence individual job search behavior. Importantly, sociologists also made this observation in France in the study *"Mon quartier, mes voisins"* (Bonneval, 2021).

Figure 2: Estimated coefficients and 95% confidence intervals for endogenous effects for three subsamples defined by built environment density

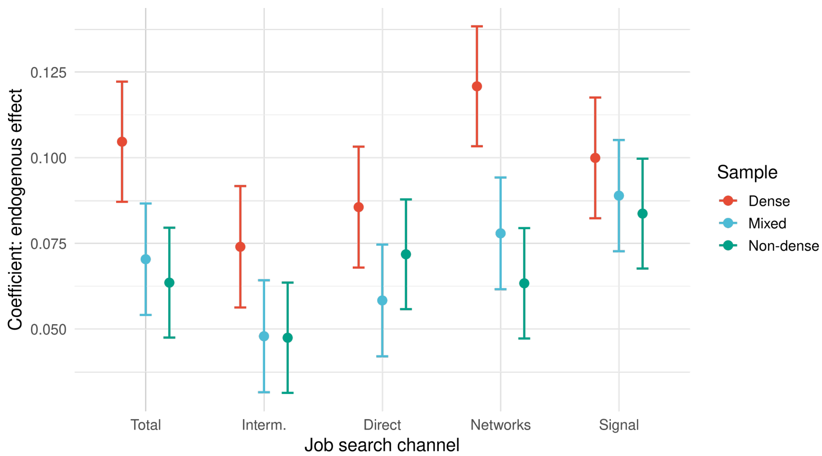
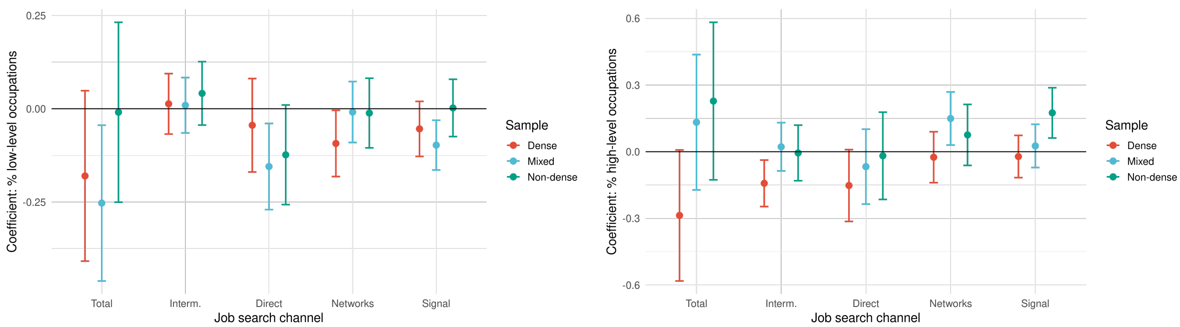


Figure 3: Estimated coefficients and 95% confidence intervals for group effects (% low-level and % high-level neighbors) for three subsamples defined by built environment density



4.4 Heterogenous effects depending on period

In a complementary analysis, we divide the estimation sample into two sub-periods. The first covers the years 2014–2016, and the second, the years 2017–2019. This additional analysis serves two purposes. First, it allows us to compare the effects of social interactions across periods in which the national economic context, particularly unemployment, differs. Indeed, according to INSEE, the national unemployment rate was slightly above 10% from 2014 to 2016, and between 8.5 and 9.5% from 2017 to 2019.[19] This significant change in the labor market context could induce changes in job search behaviors.

The second objective is to address a potential limitation of our analysis. Using a fixed effects identification strategy at the sector level means comparing unemployed individuals from the same sector but in different clusters, that were surveyed at different points in time, potentially up to five years apart. In practice, this implies that the control group consists of unemployed individuals living in the same sector who were observed in different years. This raises questions about potential changes within sectors across years. In particular, could there be local time-varying shocks affecting unobservables at the cluster level, or leading to the sorting of individuals across clusters within a sector over time? Examples of such local shocks could be the closure of a local French Employment Agency that could lead to less search via institutional intermediaries in a neighborhood. All individuals in a cluster × quarter would be simultaneously affected, creating a correlation in their behaviors. If this happened, the sector fixed effects would not correctly control for cluster-level unobservables, which would create a bias in the estimated neighborhood effects. Splitting the sample into two shorter time periods limits these concerns by comparing individuals within a narrower window of time.

For conciseness, we present here only plots of the estimated coefficients for endogenous effects (Figures 4 and 5). Table F.2 in the online Appendix presents the full set of coefficients for the corresponding estimations. We find that endogenous effects are stronger in the 2017–2019 period than in 2014–2016, with significant differences for job search through intermediaries and direct approaches. This suggests that periods with more favorable labor market conditions tend to amplify social interaction effects in job search behavior, although overall search activity is slightly — but not significantly — lower (see Table F.2 for means).

Before to comment further, we want to stress that the identification of contextual and group effects is based on the variation of the neighbors composition within the sector. By decreasing mechanically the number of clusters within each sector, the split of the sample into two subperiods makes this identification more difficult. On the main sample, we found contextual effects through an impact of the share of unemployed having never worked on search through direct contacts and total search activities. These effects are found here only during the second period. The diffusion of direct applications in neighborhoods with more newcomers to the labor market seems thus associated with the growth in new jobs.

The composition of the non-unemployed neighbors also tends to have different impacts depending on the period. In the first period, we observe a significant decrease in total

[19]Source: https://www.insee.fr/fr/statistiques/4805248

search in neighborhoods with a higher share of low-level occupations. In the second period, we observe that a higher share of low-level occupations significantly increases search through intermediaries, and a higher share of high-level occupations significantly increases search through networks. Taken together, these results suggest that, in a period where the economic situation is bad, being surrounded by neighbors with a low background on the labor market decreases search activities, possibly by a lack of role models. When the economic situation improves on the contrary, contacts with intermediaries are fostered by having neighbors employed in low-level occupations, for whom contacting an employment intermediary seems a natural approach, while having neighbors with a higher position on the labor market increases the use of networks, which are indeed more often considered by this group.

Figure 4: Estimated coefficients and 95% confidence intervals for endogenous effects for two subsamples defined by period

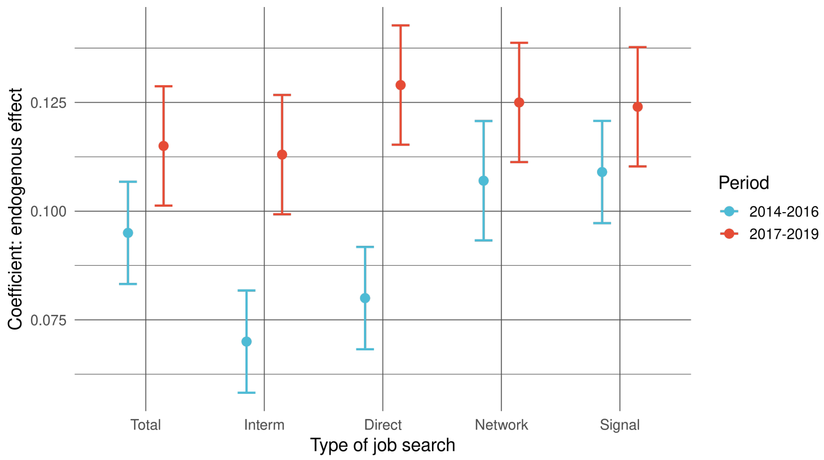
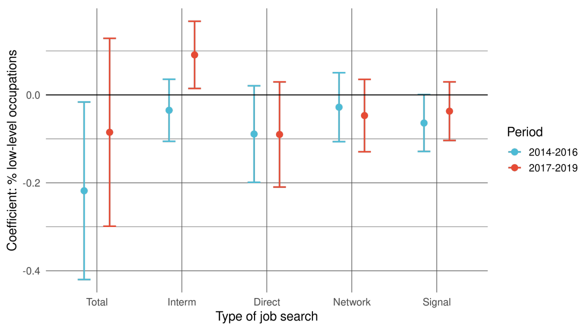
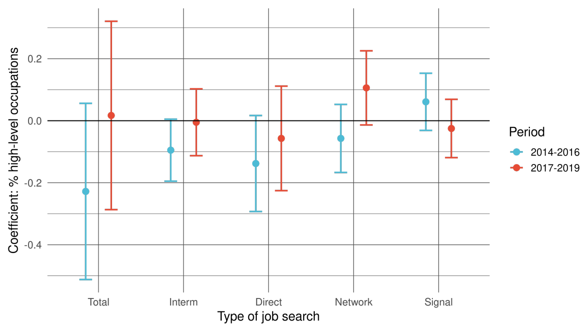


Figure 5: Estimated coefficients and 95% confidence intervals for group effects (% low-level and % high-level neighbors) for two subsamples defined by period





5 Robustness checks

In this section, we present evidence in support of the hypothesis of location exogeneity conditional on sector fixed effects, using two different tests. In the same aim, we present two robustness checks using alternative samples.

5.1 Test for the absence of sorting across clusters within sectors

Our strategy to address location endogeneity relies on the assumption that individuals are randomly distributed across clusters within sectors. Following Bayer et al. (2008), and Hémet and Malgouyres (2018) who used the same test on FLFS on another population, we indirectly test this assumption by examining whether individuals' observed characteristics are correlated with those of their neighbors once sector effects are controlled for. A near-zero correlation would support the validity of the assumption for unobservables.

For each characteristic, we first regress both the individual's value and the exclusive neighborhood average of the same variable on sector fixed effects.[20] We then regress the residuals from these two regressions on one another. The resulting R-square measures the correlation between the two deviations from the sector average, and thus the intensity of sorting on the selected observable between clusters within sectors. Because exclusive averaging induces mean reversion — high-level individuals being mechanically associated with low-level neighbors — which could lead to a systematic negative correlation between the individual and the average of her neighbors, we randomly select one individual per cluster. This procedure is repeated 1,000 times with different random draws, and the average R-square is reported.

The resulting values are presented in column (3) of Table 6 for four characteristics: education, previous occupation, citizenship, and mean age. We conduct the tests for three groups of neighbors. The first two include non-unemployed and employed neighbors — those used to compute group effects — whose results appear in Panels A and B. The third group consists of unemployed neighbors, relevant for contextual and endogenous effects, with results shown in Panel C. Each test is restricted to individuals who have at least one neighbor in the corresponding group.[21] For comparison, column (1) reports the raw R-square values without fixed effects, and column (2) shows the results when controlling for urban-unit fixed effects.[22] Column (1) values are expected to be high due to spatial sorting at the neighborhood level. Sorting between clusters within urban units remains, so that R-squares in column (2) should still be significant, while column (3) should show much lower correlations if our identification assumption holds.

Across all three neighbor groups — non-unemployed, employed, and unemployed — the R-square values tend to decline from column (1) to column (3), confirming that sorting is largely absorbed by sector fixed effects. For instance, citizenship, typically one of the most spatially segregated trait, shows correlations of 5.78 (without fixed effects) and 2.27

[20] As in the main analysis, the other household members are excluded from the neighbors' average.

[21] Three observations are lost for non-unemployed neighbors and 26 for employed neighbors. By contrast, 19,297 observations are excluded for unemployed neighbors.

[22] We also computed R-square values with municipality fixed effects, but these are similar to sector fixed effects since only large municipalities contain multiple sectors.

(with urban-unit fixed effects) for non-unemployed and unemployed neighbors, respectively, but drops to 0.14 once sector fixed effects are included. This indicates that, within sectors, individual and neighbors' citizenship are almost uncorrelated. The same pattern holds for all other characteristics, with all sector-adjusted R-square values below 0.5. These findings support the validity of our identifying assumption regarding the random distribution of individuals across clusters within sectors.[23]

5.2 Controlling for potential group endogeneity

The R-square test has a limitation, as it relies on observables rather than unobservables. An argument in favor of using observables is that they are in general major determinants of the behaviors at stake, and therefore likely to induce a strong correlation if the identification strategy is weak (Altonji et al., 2005). Still, one could ask whether the location exogeneity hypothesis is formally satisfied, that is, whether it holds for unobservables.

In the network effects literature, some recent models have been proposed to deal with network formation, on the basis of which network endogeneity can be dealt with (Arduini et al., 2015; Auerbach, 2022). In a nutshell, the idea consists in first estimating a network formation model, which allows to evaluate unobserved heterogeneity traits responsible for sorting on the network. These estimated heterogeneity traits are then included in the main model to control for the specificities of the network the individuals belong to. Following this idea, we provide a robustness check based on estimating a dyadic network formation model following Graham (2017) and Houndetoungan (2024). In our setting, estimating the network formation model amounts to estimating the probability that two individuals in the sample live in the same cluster, rather than in separate clusters within the same sector. The links between individuals living in the same cluster are assumed to be symmetric. The probability for a dyad to live in the same cluster can thus be expressed as:

$$P(a_{ij} = 1 | v_{ij}, \mu_i, \nu_j) = \Phi(v'_{ij}\psi + \mu_i + \nu_j) \tag{2}$$

where v_{ij} is a measure of social distance between agents i and j that drives the likelihood to live in the same cluster, μ_i and ν_j are individual heterogeneity fixed effects involved in the cluster choice, ψ is a parameter to be estimated and Φ is the logistic cdf. The measure of social distance is represented here by a vector of observed covariates at the pair of individuals level, namely a set of dummies for both individuals being former high-skilled workers, both having never worked, both having a child, both being foreigners, and the difference in their unemployment duration in months. Given the symmetry of the links, a single fixed effect μ is estimated for each individual. It accounts for all individual unobservables that affect location choice in a cluster within a specific sector.

In a second stage, following Johnsson and Moon (2021), our main model is augmented by including a smooth transformation (namely a piecewise cubic polynomial approximation) of the individual fixed effect derived from the network formation model, and estimated.[24]

[23] As explained in Subsection 2.1, repeated neighbor pairs were dropped to avoid within-sector correlation. We ran the R-square tests on the full sample before excluding the pair repetitions. For unemployed neighbors, the presence of repeated pairs slightly raises correlations but, except for the executive category, all R-square values remain below 1, suggesting that our sample selection could be less stringent without biasing the results.

[24] This transformation allows for a flexible functional form between Y_{igst} in Equation 1 and the individual heterogeneity trait. These estimations are performed using the `homophily` function from CDatanet

Table 6: Correlation between individual and neighbors' average characteristics

	Fixed effects		
	None	Urban unit	Sector
Panel A: All neighbors			
Education			
Low-level diploma	8.045	4.939	0.492
Baccalaureate	0.198	0.117	0.004
High-level diploma	8.858	5.576	0.354
Previous occupation			
Indep. worker	0.013	0.001	0.015
Executive	6.307	3.785	0.351
Intermediate prof.	0.361	0.241	0.002
Blue/white-collar workers	2.282	1.651	0.199
Citizenship			
French	5.785	2.763	0.139
Foreign	5.885	2.804	0.142
Mean age	0.901	0.732	0.144
Obs. (cluster × quarter)		31,343	
Panel B: Employed neighbors			
Education			
Low-level diploma	6.317	3.933	0.363
Baccalaureate	0.043	0.018	0.008
High-level diploma	7.295	4.530	0.240
Previous occupation			
Indep. worker	0.029	0.003	0.008
Executive	6.348	3.985	0.356
Intermediate prof.	0.211	0.146	0.001
Blue/white-collar workers	3.721	2.396	0.292
Citizenship			
French	4.933	2.303	0.140
Foreign	4.968	2.324	0.143
Mean age	0.993	0.677	0.109
Obs. (cluster × quarter)		31,320	
Panel C: Unemployed neighbors			
Education			
Low-level diploma	1.647	0.848	0.029
Baccalaureate	0.008	0.001	0.138
High-level diploma	2.013	1.161	0.006
Previous occupation			
Indep. worker	0.083	0.023	0.055
Executive	0.993	0.523	0.166
Intermediate prof.	0.117	0.061	0.093
Blue/white-collar workers	0.627	0.321	0.013
Has never worked	0.234	0.115	0.006
Citizenship			
French	2.270	0.839	0.011
Foreign	2.267	0.829	0.013
Mean age	0.185	0.050	0.072
Obs. (cluster × quarter)		12,049	

Note: Each cell in this table reports a R-square estimated as follows: on a randomly drawn sample with one observation by cluster × quarter, we regress both an individual's characteristic and the exclusive average of the same characteristic among neighbors in the cluster × quarter on fixed effects. The residuals of these two regressions are then regressed on each other. The procedure is repeated on 1,000 random samples and the mean R2 are presented here. In column 1, individual's characteristic is directly regressed on the average among neighbors. The fixed effects are at the urban unit in column 2 and at the sector level in column 3. R-squares are expressed in percentages, so that 8.045 means that the RHS variable explains 8.045 percent of the LHS variable's variance. Panel A corresponds to the test in which the cluster average is computed on non-unemployed neighbors. In panel B, the cluster average is computed on employed neighbors, and in panel C the cluster average is computed on unemployed neighbors. Only clusters with at least one neighbor can be used in the test. The sample from which these draws are made consists of 49,696 unemployed observations, in 31,346 clusters × quarter. 31,343 clusters × quarter have at least one non-unemployed individual, 31,320 at least one employed, and 12,049 have more than one unemployed neighbor.

This method is analog in spirit to using a control function and allows us to control for cluster endogeneity, that is, the correlation between the neighbors' unobservables, and the unobservables impacting job search behavior. These unobservables can be related for example to the level of unobserved human capital. By definition, the network formation model cannot be implemented for isolated individuals. Table 7 shows the results of this augmented model estimated on the sample of non-isolated individuals in Panel A. For comparison, the results of the main model on the same sample are presented in Panel B.

One first notes that controlling for cluster endogeneity does not cancel out the significance nor changes the coefficients of the endogenous effects, compared to the main model results on the same sample. We also find very close contextual and group effects. Moreover, log-likelihoods of the models in Panel A and B are very similar. The stability of coefficients and log-likelihoods tends to support the idea that including individual unobserved heterogeneity does not add anything in terms of identification, and that location endogeneity is adequately dealt with on the sample of non-isolated individuals with our main identification strategy.

We also emphasize that including a network formation model helps address potential sorting induced by time-varying shocks within sectors, as discussed in Subsection 4.4. Such shocks could influence the composition of individuals across clusters within a sector over time. Examples include public housing construction or changes in transportation access within a sector. By accounting for unobservables that affect the choice of living in one cluster versus another within the same sector, this specification controls for potential temporal changes across clusters. Our results indicate that these potential sorting effects do not appear to affect the estimated neighborhood effects.

In conclusion, the results from the network formation model confirm that our main identification strategy adequately accounts for location endogeneity. Our preferred specification still remains the main model estimated on the full sample, including unemployed individuals without unemployed neighbors. This approach avoids selection bias and enhances the identification of the coefficients of individual characteritics, thereby improving the estimation of neighborhood effects.[25] In addition, isolated unemployed individuals contribute to the estimation of group effects, which may explain some differences in the corresponding coefficients between Table 4 and Table 7.

R package written by Aristide Houndetoungan.

[25]Table I.1 in the online Appendix shows that isolated unemployed individuals tend to live in less dense and possibly more privileged environments. Their potential behavioral specificities are accounted for in the main results through the dummy variable *has unemployed neighbors*.

Table 7: Results with and without controls for unobserved heterogeneity - Non-isolated sample

	Explained variable				
	Total	Direct	Network	Signal	Interm.
	(1)	(3)	(4)	(5)	(2)
Panel A: with network formation model					
Endogenous effects					
Un. neighbors' average intensity	0.050***	0.056***	0.060***	0.026***	0.040***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	−0.016	0.003	0.013	0.001	−0.032
	(0.035)	(0.014)	(0.011)	(0.012)	(0.019)
% has never worked	0.058	−0.001	0.014	0.008	0.038
	(0.047)	(0.018)	(0.015)	(0.017)	(0.026)
Group effects *(among non-unemp. neighb.)*					
% employed	−0.013	0.017	−0.025	−0.011	0.006
	(0.114)	(0.044)	(0.036)	(0.040)	(0.062)
% low-level occupations	−0.309***	−0.089**	−0.045	−0.004	−0.179***
	(0.092)	(0.035)	(0.029)	(0.033)	(0.051)
% high-level occupations	−0.202	0.043	0.072	−0.104**	−0.219***
	(0.139)	(0.054)	(0.044)	(0.049)	(0.077)
Indiv. characteristics	Yes	Yes	Yes	Yes	Yes
Indiv. FE (network formation)	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	−57,085	−30,886	−25,379	−28,355	−40,628
Panel B: without network formation model					
Endogenous effects					
Un. neighbors' average intensity	0.050***	0.056***	0.060***	0.026***	0.041***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	−0.018	0.004	0.013	0.00001	−0.033*
	(0.035)	(0.013)	(0.011)	(0.012)	(0.019)
% has never worked	0.055	0.038	−0.0007	0.006	0.038
	(0.047)	(0.018)	(0.015)	(0.017)	(0.026)
Group effects *(among non-unemp. neighb.)*					
% employed	−0.017	0.018	−0.027	−0.013	0.005
	(0.114)	(0.044)	(0.036)	(0.040)	(0.062)
% low-level occupations	−0.314***	−0.084**	−0.047	−0.002	−0.178***
	(0.092)	(0.035)	(0.029)	(0.033)	(0.051)
% high-level occupations	−0.193	0.041	0.076*	−0.101**	−0.215***
	(0.139)	(0.054)	(0.044)	(0.049)	(0.077)
Indiv. characteristics	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	−57,092	−30,895	−25,388	−28,369	−40,638
N (Obs./ Sectors/ Clusters x t/ Indiv.)	30,399 / 2,726 / 12,049 / 26,029				
Dependent variable mean	3.62	0.94	0.47	0.73	1.49
Dependent variable s.d.	2.04	0.79	0.65	0.70	1.10

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents the estimated coefficients for the variables of interest in Equation 1, estimated on the main estimation sample after dropping clusters with only one unemployed individual. Panel A includes individual fixed effects derived from a network formation model. See Table B.1 and Table 3 for a detailed presentation of the independent variables.

5.3 Discarding public housing clusters

The French housing market has a large share of public housing, which represented 15.6% of the housing stock in 2021.[26] Public housing houses mostly low-income households and has a higher share of low-skilled and unemployed individuals compared to the rest of the housing stock. Most of public housing is built as large multi-family buildings. Given the spatial structure of the FLFS sample, in which a cluster of surveyed households is likely to belong to a given building, it could be the case, especially in dense urban areas, that some clusters within a sector are made of public housing only, while others are made of private housing. As sorting between these two parts of the housing stock is not random, there could be some systematic variation in surveyed households in *"public housing clusters"* as compared to *"private housing clusters"* within the same sector, that would call into question our strategy to deal with location endogeneity. This motivates a robustness check which consists in removing from the estimation sample all clusters in which at least one housing unit is public housing. In doing so, our identification strategy amounts to comparing, within sectors, clusters made of private housing only.

Results in Panel A of Table 8 show that endogenous effects remain significant, despite the increase in standard errors resulting from the smaller sample size, which is reduced by about one third in both the number of individuals and clusters. As in the main results, endogenous effects are the strongest for search through networks and signals. For contextual effects, the two coefficients related to the share of unemployed neighbors who have never worked are no longer significant. In contrast, the effects of the share of unemployed neighbors who previously held low-skilled jobs increase and become significant for direct contacts with employers and total search activities. These changes might reflect the altered sample composition: restricting the sample to clusters of private housing only selects individuals with more favorable characteristics.[27] Regarding group effects, recall that the average characteristics of non-unemployed neighbors are constant within a cluster, so their identification relies on cluster-level variation within sectors. The reduction in the number of clusters per sector (see Figure J.1 in the online Appendix) weakens this variation, which may explain why group effects significant in the main results are no longer detected in this restricted sample.

In summary, these additional results show, particularly for the endogenous effects, that our main findings are not driven by the comparison between households belonging to the two segments of the housing market.

[26]https://www.statistiques.developpement-durable.gouv.fr/le-parc-locatif-social-au-1er-janvier-2021

[27]Columns A and B of Table I.2 show a decrease of more than three percentage points in the share of non-French citizens or individuals of non-French origin, a drop in the share with low-level diplomas, and fewer residents in high-rise housing projects.

Table 8: Discarding public housing clusters or heterogenous sectors

	Explained variable				
	Total	Direct	Network	Signal	Interm.
	(1)	(2)	(3)	(4)	(5)
Panel A: Discarding public housing clusters					
Endogenous effects					
Un. neighbors' average intensity	0.092***	0.094***	0.097***	0.109***	0.074***
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	−0.086**	−0.064***	0.006	−0.005	−0.018
	(0.043)	(0.024)	(0.017)	(0.014)	(0.015)
% has never worked	0.056	0.026	0.021	0.015	−0.003
	(0.060)	(0.034)	(0.023)	(0.019)	(0.021)
Has unemp. neighbor (0/1)	−0.334***	−0.123***	−0.099***	−0.065***	−0.053***
	(0.038)	(0.021)	(0.015)	(0.012)	(0.014)
Group effects *(among non-unemp. neighb.)*					
% employed	0.003	−0.012	0.039	−0.024	−0.0001
	(0.110)	(0.061)	(0.043)	(0.036)	(0.039)
% low-level occupations	−0.091	−0.021	0.0005	−0.044	−0.024
	(0.096)	(0.053)	(0.037)	(0.031)	(0.034)
% high-level occupations	0.013	−0.027	0.062	0.017	−0.039
	(0.121)	(0.067)	(0.047)	(0.039)	(0.042)
Indiv. characteristics	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	−54,332	−38,687	−29,461	−24,526	−26,867
N (Obs./ Sectors/ Clusters x t/ Indiv.)	28,882 / 2,517 / 20,385 / 18,560				
Dependent variable mean	3.74	1.54	0.99	0.51	0.70
Dependent variable s.d.	2.04	1.11	0.80	0.66	0.70
Panel B: Removing heterogenous sectors					
Endogenous effects					
Un. neighbors' average intensity	0.075***	0.071***	0.084***	0.088***	0.052***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	−0.019	−0.027	0.002	0.012	−0.001
	(0.034)	(0.019)	(0.013)	(0.011)	(0.012)
% has never worked	0.074	0.036	0.014	0.017	0.009
	(0.047)	(0.026)	(0.018)	(0.015)	(0.017)
Has unemp. neighbor (0/1)	−0.302***	−0.104***	−0.076***	−0.065***	−0.052***
	(0.032)	(0.017)	(0.012)	(0.010)	(0.011)
Group effects *(among non-unemp. neighb.)*					
% employed	0.016	0.029	0.025	−0.024	−0.014
	(0.084)	(0.046)	(0.032)	(0.027)	(0.029)
% low-level occupations	−0.202***	−0.122***	−0.018	−0.067***	0.008
	(0.071)	(0.039)	(0.027)	(0.023)	(0.025)
% high-level occupations	0.013	−0.084	0.109***	0.043	−0.057
	(0.097)	(0.053)	(0.037)	(0.031)	(0.034)
Indiv. characteristics	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	−85,151	−60,626	−46,204	−38,314	−42,402
N (Obs./ Sectors/ Clusters x t/ Indiv.)	43,848 / 2,631 / 28,326 / 29,455				
Dependent variable mean	3.68	1.51	0.96	0.49	0.72
Dependent variable s.d.	2.04	1.10	0.80	0.66	0.70

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents the estimated coefficients for the variables of interest in Equation 1, estimated on the sample without public housing clusters (Panel A) and the sample that without heterogenous sectors (Panel B). See Table B.1 and Table 3 for a detailed presentation of the independent variables.

5.4 Discarding heterogenous sectors

The random location choice hypothesis could be challenged in sectors with striking quality differences across clusters, for example in cases in which moving from one street to the next implies environments that differ a lot. To tackle this possible concern, we delete sectors with a high variability in the share of high-level occupations — a criteria known to adequately reflect the social quality of the local environment. More specifically, we drop sectors where the coefficient of variation across clusters of this share is above 1.5 — a value which corresponds to a clear break in the estimation sample. This selection amounts to droping 9.5% of the sectors from the main sample.

Panel B of Table 8 presents the results of the main model estimated on this restricted sample. Endogenous effects remain very similar to those reported in Table 4. Since the sample restriction involves discarding entire sectors rather than clusters within sectors, the identification of group effects is not strongly affected as it was when clusters with public housing were removed. The strong negative impact of neighbors in low-level occupations on total search, direct contacts with employers, and search through signals remains significant. The positive effect of neighbors in high-level occupations on search through networks is even stronger. Finally, the coefficients for the share of unemployed neighbors who have never worked, affecting direct search and total search activities, decline relative to the main results and become insignificant.

Overall, this robustness check suggests that our results are not affected by the existence of some spatial sorting within heterogeneous sectors, and supports pur main findings. Moreover, by removing sectors with high variation of socio-economic characteristics across clusters, we eliminate sectors that may have experienced a significant social composition change over time, without changing the main results. This observation again reduces the potential concerns about time-varying shocks and changes in neighborhood quality mentioned in Subsection 4.4.

6 Conclusion

This paper aims at measuring the impacts of interactions with neighbors in the job search behaviors of unemployed individuals. Search behaviors are known to play a central role in return to employment and labor market outcomes. We use data from the FLFS that allows us to identify four job search channels, namely search through direct contacts with employers, search through networks, search through signalling one's search, and search through intermediaries. The data also allows us to identify two nested levels of neighborhoods at a very precise level by surveying clusters of 20 contiguous dwellings grouped into sectors. We implement a model of endogenous, contextual and group effects *à la* Manski (1993), and apply it to the four job search channels and total search activities. Following Lee (2007) and Boucher et al. (2014), we address the reflection issue that threatens the identification of endogenous and contextual effects by relying on exclusive averaging and variations in group size. Similar to the approach in Bayer et al. (2008), we control for the non-random sorting of individuals into neighborhoods by including sector fixed effects. We conduct a series of robustness checks to support our identification strategy, namely by testing for the absence of correlation of observables, including a network formation model, and restricting the sample to more homogenous sectors.

We cannot make any definitive interpretation of the results we find, as we are limited to the available information we have in FLFS. In particular, the information regarding job search behaviors does not allow to measure search intensity. Still, we think the FLFS provides a unique data source to study job search behaviors, and their impact by neighborhood effects, because it includes very detailed types of search activities, its sampling procedure follows two nested neighborhood levels, and its large sample size provides statistical power.

Our work contributes to the literature on neighborhood effects in labor market outcomes. We find important endogenous effects for the four job search channels we consider, as well as for total search intensity. These findings suggest the existence of a social multiplier effect: the more unemployed neighbors search through a specific channel, the higher the incentives to act similarly. The stronger impact of search through networks compared to other channels, and the weaker impact of searching through intermediaries, might signal the impact of information exchange rather than social pressure or social norms, which would affect all channels similarly. We also observe group effects. A higher proportion of neighbors employed in low-skilled jobs decreases the use of direct contacts with employers and signals, while a higher proportion of neighbors employed in high-skilled jobs increases the use of personal or professional contacts. We interpret these results as showing that the quality of connections that employed neighbors have to the labor market affects the type of information or support they can provide to the unemployed.

A heterogeneity analysis shows that these effects are stronger in denser environments. This result challenges the idea that these environments are synonymous with anonymity, but it is consistent with the idea that encounters between neighbors are more likely when density is higher. Using an alternative measure that gives more weight to more efficient types of action yields slightly lower neighborhood effects, suggesting some inefficiency in the impact of neighborhood effects.

Several papers underline the existence of neighborhood effects in out-of-unemployment transitions. We believe we are the first to focus on the pre-hiring stage. Moreover, the strong social interactions results for search through networks can be connected to the ast literature underlining the higher efficiency of this channel (Granovetter, 1995; Caliendo et al., 2011; Cingano and Rosolia, 2012). Together, these two observations regarding job search would suggest an additional factor explaining urban unemployment inequalities. In neighborhoods with unemployed individuals actively searching through networks, the social multiplier effect would lead to an equilibrium with faster return to employment. At this stage however, we did not find evidence that the job search channels which are the most efficient to find a job are the most likely to be influenced by neighbors' behaviors. Further research would thus be necessary to connect these two strands of literature. It would also be very useful to know more about the relative contributions of social pressure, spread of information, imitation behind the neighborhood effects that we find.

We contribute also more generally to the literature on job search behaviors by providing evidence on the influences shaping the use of different job search channels. In the French context, the use of personal and professional contacts in job search seems associated with higher-skilled positions. The same hold for direct contacts with potential employers, which requires a minimum knowledge of the job market. On the contrary, turning to institutional intermediaries is more common for lower-skilled individuals and in less privileged environments.

Our findings on the prevalence of the different social interaction effects have implications for public policies. While the results related to group and contextual effects seem to be in favor of social mixing policies (e.g. the French SRU law (*Loi Solidarité et Renouvellement Urbain*) or the US Moving To Opportunity program, they are not very strong, and a more effective policy to us would thus be to target directly a change in behaviors. More specifically, the endogenous effects seem to underline the need for policies that would promote the spread of information among unemployed neighbors i.e. a counseling policy or the setting up of discussion groups among unemployed neighbors by the local employment agency. One example of such policy are the young job search seekers clubs (*Club jeunes chercheurs d'emploi*) in France. These pilot experiments were implemented in deprived neighborhoods by the French Employment Agency and aimed at fostering job search among young unemployed through local interaction groups. Blasco et al. (2015) assess the effectiveness of such policy and find positive peer effects that translate in higher search effort.

References

Addison, J. T., and Portugal, P. (2002). Job search methods and outcomes. *Oxford Economic Papers*, *54(3)*, 505–533.

Akerlof, G. A. (1980). A theory of social custom, of which unemployment may be one consequence. *The Quarterly Journal of Economics*, *94*(4), 749.

Altonji, J. G., Elder, T. E., and Taber, C. R. (2005). Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy*, *113*(1), 151–184.

Andersson, E. (2004). From valley of sadness to hill of happiness: The significance of surroundings for socioeconomic career. *Urban Studies*, *41*(3), 641–659.

Arduini, T., Pattachini, E., and Rainone, E. (2015). Parametric and semiparametric iv estimation of network models with selectivity. *Einaudi Institute for Economics and Finance (EIEF)*.

Auerbach, E. (2022). Identification and Estimation of a Partially Linear Regression Model Using Network Data. *Econometrica*, *90*(1), 347–365.

Authier, J.-Y., and Cayouette-Remblière, J. (2021). Les conversations. In J.-Y. Authier and J. Cayouette-Remblière (Eds.), *Les formes contemporaines du voisinage : Espaces résidentiels et intégration sociale* (pp. 79–98). Ined.

Bachmann, R., and Baumgarten, D. (2013). How Do The Unemployed Search For a Job? – Evidence From The EU Labour Force Survey. *IZA Journal of European Labor Studies*, *2*(1), 2-22.

Bayer, P., Ross, S. L., and Topa, G. (2008). Place of work and place of residence: Informal hiring networks and labor market outcomes. *Journal of Political Economy*, *116*(6), 1150-1196.

Beam, E. A. (2021). Search costs and the determinants of job search. *Labour Economics*, *69*.

Blasco, S., Crépon, B., Skandalis, D., Uhlendorff, A., Van Den Berg, G., Alberola, E., and Aventur, F. (2015). *Club jeunes chercheurs d'emploi. Évaluation d'une action pilote.*

Boeri, T., De Philippis, M., Patacchini, E., and Pellizzari, M. (2015). Immigration, Housing Discrimination and Employment. *The Economic Journal*, *125*, 82–114.

Bonneval, L. (2021). Visites et échanges de services. In J.-Y. Authier and J. Cayouette-Remblière (Eds.), *Les formes contemporaines du voisinage : Espaces résidentiels et intégration sociale* (pp. 63–78). Ined.

Boucher, V., Bramoullé, Y., Djebbari, H., and Fortin, B. (2014). Do peers affect student achievement? Evidence from Canada using group size variation. *Journal of Applied Econometrics*, *29*(1), 91-109.

Bramoullé, Y., Djebbari, H., and Fortin, B. (2009). Identification of peer effects through social networks. *Journal of Econometrics*, *150*(1), 41-55.

Böheim, R., and Taylor, M. (2001). Job Search Methods, Intensity and Success in Britain in The 1990s. *Department of Economics, Johannes Kepler University of Linz, Working Paper No. 0206*.

Caliendo, M., Cobb-Clark, D. A., and Uhlendorff, A. (2015). Locus of control and job search strategies. *The Review of Economics and Statistics*, *97*(1), 88–103.

Caliendo, M., Schmidl, R., and Uhlendorff, A. (2011). Social networks, job search methods and reservation wages: Evidence for Germany. *International Journal of Manpower*, *32*(7), 796–824.

Chyn, E., and Katz, L. F. (2021). Neighborhoods Matter: Assessing the Evidence for Place Effects. *Journal of Economic Perspectives*, *35*(4), 197–222.

Cingano, F., and Rosolia, A. (2012). People I know: Job search and social networks. *Journal of Labor Economics*, *30*(2), 291–332.

Cunha, F., Heckman, J. J., and Schennach, S. M. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, *78*(3), 883–931.

Damm, A. (2014). Neighborhood quality and labor market outcomes: Evidence from quasi-random neighborhood assignment of immigrants. *Journal of Urban Economics*, *79*(C), 139–166.

Davezies, L., D'Haultfoeuille, X., and Fougère, D. (2009). Identification of peer effects using group size variation. *The Econometrics Journal*, *12*(3), 397–413.

Eilers, L., Paloyo, A. R., and Bechara, P. (2021). The effect of peer employment and neighborhood characteristics on individual employment. *Empirical Economics*, *62*, 1885–1908.

Galster, G. C. (2024). *Making Our Neighborhoods, Making Our Selves.* University of Chicago Press.

Graham, B. S. (2017). An Econometric Model of Network Formation With Degree Heterogeneity. *Econometrica*, *85*(4), 1033–1063.

Granovetter, M. S. (1995). *Getting a Job: A Study Of Contacts And Careers* (2nd ed.). Chicago: University of Chicago Press.

Grinblatt, M., Keloharju, M., and Ikäheimo, S. (2008). Social influence and consumption: Evidence from the automobile purchases of neighbors. *The Review of Economics and Statistics*, *90*(4), 735–753.

Hellerstein, J. K., Kutzbach, M. J., and Neumark, D. (2014). Do labor market networks have an important spatial dimension? *Journal of Urban Economics*, *79*, 39–58.

Hellerstein, J. K., McInerney, M., and Neumark, D. (2011). Neighbors and coworkers: The importance of residential labor market networks. *Journal of Labor Economics*, *29*(4), 659–695.

Hémet, C., and Malgouyres, C. (2018). Diversity and employment prospects: Neighbors matter! *Journal of Human Resources*, *53*(3), 825–858.

Hémet, C., and Malgouyres, C. (2019). The Strength and Use of Local Referral Networks: Evidence from France. *Mimeo, Paris School of Economics*.

Holzer, H. (1988). Search method use by unemployed youth. *Journal of Labor Economics*, *6*(1), 1–20.

Houndetoungan, E. A. (2024). Count Data Models with Social Interactions Under Rational Expectations. *Mimeo, THEMA, CY Cergy Paris Université*.

Ioannides, Y. M., and Loury, L. D. (2004). Job information networks, neighborhood effects, and inequality. *Journal of Economic Literature*, *42*(4), 1056–1093.

Jackson, M. O., Rogers, B. W., and Zenou, Y. (2020). Networks: An economic perspective. In *The Oxford Handbook of Social Networks* (p. 535-562). ed. by R. Light and J. Moody, Oxford University Press.

Jahn, E., and Neugart, M. (2020). Do neighbors help finding a job? Social networks and labor market outcomes after plant closures. *Labour Economics*, *65*.

Johnsson, I., and Moon, H. R. (2021, May). Estimation of Peer Effects in Endogenous Social Networks: Control Function Approach. *The Review of Economics and Statistics*, *103*(2), 328–345.

Lee, L.-F. (2004). Asymptotic distributions of quasi-maximum likelihood estimators for spatial autoregressive models. *Econometrica*, *72*(6), 1899–1925.

Lee, L.-F. (2007). Identification and estimation of econometric models with group interactions, contextual factors and fixed effects. *Journal of Econometrics*, *140*(2), 333–374.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, *60*(3), 531.

Merlino, L. P. (2014). Formal and informal job search. *Economics Letters*, *125*(3), 350–352.

Moffitt, R. (2001). Policy interventions, low-level equilibria, and social interactions. In *Social Dynamics* (pp. 45–92). ed. by S. Durlauf and P. Young, MIT Press: Cambridge, MA.

Nicodemo, C., and García, G. A. (2015). Job search channels, neighborhood effects, and wages inequality in developing countries: The Colombian case. *The Developing Economies*, *53*(2), 75–99.

Patacchini, E., and Zenou, Y. (2005). Spatial mismatch, transport mode and search decisions in England. *Journal of Urban Economics*, *58*(1), 62–90.

Patacchini, E., and Zenou, Y. (2006). Search activities, cost of living and local labor markets. *Regional Science and Urban Economics*, *36*(2), 227–248.

Piercy, C. W., and Lee, S. K. (2019). A typology of job search sources: Exploring the changing nature of job search networks. *New Media & Society*, *21*(6), 1173–1191.

Pissarides, C. A. (2000). *Equilibrium Unemployment Theory* (2nd ed.). Cambridge, Mass: MIT Press.

Schmutte, I. M. (2015). Job referral networks and the determination of earnings in local labor markets. *Journal of Labor Economics*, *79*(1), 1–32.

Solignac, M., and Tô, M. (2018). Do workers make good neighbours? The impact of local employment on young male and female entrants to the labour market. *Annals of Economics and Statistics*(130), 167–198.

Stupnytska, Y., and Zaharieva, A. (2015). Explaining U-shape of the referral hiring pattern in a search model with heterogeneous workers. *Journal of Economic Behavior & Organization*, *119*, 211–233.

Topa, G. (2001). Social interactions, local spillovers and unemployment. *The Review of Economic Studies*, *68*(2), 261–295.

Topa, G., and Zenou, Y. (2015). Neighborhood and network effects. In G. Duranton, J. V. Henderson, and W. C. Strange (Eds.), *Handbook of Regional and Urban Economics* (Vol. 5, pp. 561–624). Elsevier.

Vázquez-Grenno, J. (2018). Job search strategies in times of crisis: Natives and immigrants in Spain. *The Manchester School*, *86*(2), 248–278.

Wilson, W. J. (1987). *The Truly Disadvantaged: The Inner City, The Underclass, and Public Policy.* Chicago: Univ. of Chicago Press.

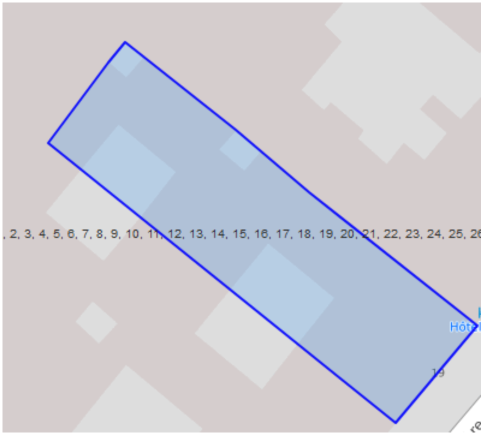
Wydick, B., Karp Hayes, H., and Hilliker Kempf, S. (2011). Social Networks, Neighborhood Effects, and Credit Access: Evidence from Rural Guatemala. *World Development*, *39*(6), 974–982.

Zenou, Y. (2015). A dynamic model of weak and strong ties in the labor market. *Journal of Labor Economics*, *33*(4), 891–932.

Main appendix

A Examples of clusters: urban vs. less urbanized (rural) areas

Figure A.1: Example of a cluster in Paris - 28 dwellings part of the same building



Source: INSEE

Figure A.2: Example of a cluster in a rural community

Source: INSEE

B Variables definition and descriptive statistics

Table B.1: Variable definition - Individual characteristics

Variables	Definition
Age	- *15-29*: being aged between 15 and 29. - *30-39*: being aged between 30 and 39. - *40-49*: being aged between 40 and 49. - *50-59*: being aged between 50 and 59. - *Above 60*: being more than 60 y.o. The reference is 40-49.
Sex (female)	Male (reference) or female.
Child	Having one child or more.
Foreigner	Having a non-French nationality.
Level of education	- *Low-level diploma* includes vocational diploma, middle school certificate, primary school certificate and no diploma. - *Baccalaureate* corresponds to the three tracks of the French high-school diploma: the general, technical and professional baccalaureate. It is the reference in the regressions, together with 0.4% of observations with missing values. - *High-level diploma* includes graduate and post-graduate degrees.
Previous occupation	- *Low-level occupations*: ex low-level white collars and blue-collar workers - *High-level occupations*: senior executives and higher intellectual occupations - *Has never worked*: unemployed who have never worked - *Other occupation*: intermediate occupations, independent workers and farmers. It is the reference in the regressions, together with 0.8% of observations with missing values.
Partner's employment status	A couple is defined by the *INSEE* as two persons aged 15 or over who live in the same dwelling and currently declare themselves to be in a relationship, regardless of their legal status. Having a partner follows from this definition. - *Employed partner*: having a partner who is employed - *Unemployed partner*: having a partner who is unemployed - *Inactive partner*: having a partner who is inactive - *No partner*: having no partner. It is the reference in the regression, along with 0.2% of observations with missing information.
Quarter dummies	Dummies Q12014 to Q42019, with Q12016 the reference.
Dwelling's architectural environment	Type of urban fabric surrounding the dwelling, in five categories: - *Scattered houses outside of urban agglomerations*, - *Houses in an (sub-)urban environment*, - *Flats in urban areas*, - *Flats in high-rise housing projects*, - *Mixed housing*.
Type of area	Category the commune belongs to according to INSEE definition: - *Rural municipalities*: less than 2,000 inhabitants - Other municipalities classified depending on the size of the urban unit they belong to: . *less than 10,000 inhabitants*, . *10,000 to 50,000 inhabitants*, . *50,000 to 100,000 inhabitants*, . *100,000 to 200,000 inhabitants*, . *more than 200,000 inhabitants (except Paris)*, . *Paris urban unit*

Table B.2: Descriptive statistics (in %) on the estimation sample and full sample

	Estimation sample[a]	Full sample[b]
Age		
Age 15+	38.9	39.4
Age 30+	22.1	22.3
Age 40+	19.1	18.9
Age 50+	16.6	16.2
Age 60+	3.3	3.1
Female	48.9	49.0
Has one child or more	37.8	38.3
Nationality		
French	87.6	86.9
Foreigner	12.4	13.1
Education[c]		
Low-level diploma	52.1	53.3
Baccalaureate	22.1	21.9
High-level diploma	25.3	24.4
Missing	0.5	0.4
Previous occupation[c]		
Farmers	0.1	0.1
Independent workers	2.9	2.8
High-level occupations	7.2	6.7
Intermediate occupations	14.3	13.9
Low-level occupations	57.8	58.1
Unemployed (have never worked)	17.0	17.6
Missing	0.7	0.7
Partner's employment status[c]		
Employed partner	30.3	29.6
Unemployed partner	3.6	3.9
Inactive partner	10.7	11.0
No partner	55.4	55.4
Missing	0.0	0.0
Dwelling's architectural environment[c]		
Scattered houses outside of urban agglomerations	8.0	7.6
Houses in an urban or sub-urban environment	31.6	30.7
Flats in high-rise housing projects	16.1	17.7
Other flats in urban areas	24.6	24.3
Mixed housing	5.0	5.1
Missing	14.7	14.7
Type of area		
Rural municipalities	14.1	13.2
Urb. unit less than 10,000 inhabitants	7.8	7.4
Urb. unit 10,000 to 50,000 inhabitants	10.1	10.3
Urb. unit 50,000 to 100,000 inhabitants	9.1	9.1
Urb.unit 100,000 to 200,000 inhabitants	7.4	7.8
Urb. unit more than 200,000 inhabitants (except Paris)	33.3	34.0
Paris urban unit	18.2	18.0
N individuals	33,735	38,023
N observations	49,696	74,151

Notes: These descriptive statistics are based on one observation per individual.
[a] The estimation sample is derived from the full sample, after discarding pairs of neighbors observed at different quarters, following the procedure described in subsection 2.1. [b] The full sample includes all unemployed individuals responding to the conditions exposed in subsection 2.1.
[c] See Table B.1 for the definition of variables.

C Control variables: main model

Table C.1: Main regression results

	Explained variable				
	Total	Direct	Network	Signal	Interm.
	(1)	(2)	(3)	(4)	(5)
Endogenous effects					
Un. neighbors' average intensity	0.079***	0.072***	0.086***	0.091***	0.056***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	−0.018	−0.026	−0.002	0.011	0.003
	(0.033)	(0.018)	(0.013)	(0.010)	(0.011)
% has never worked	0.080*	0.050**	0.008	0.016	0.009
	(0.044)	(0.024)	(0.017)	(0.014)	(0.015)
Has unemp. neighbor (0/1)	−0.309***	−0.106***	−0.073***	−0.063***	−0.057***
	(0.031)	(0.017)	(0.009)	(0.009)	(0.010)
Group effects *(among non-unemp. neighb.)*					
% employed	0.014	0.043	0.021	−0.028	−0.023
	(0.078)	(0.044)	(0.031)	(0.025)	(0.027)
% low-level occupations	−0.190**	−0.110***	−0.042	−0.055***	0.018
	(0.067)	(0.036)	(0.025)	(0.021)	(0.023)
% high-level occupations	0.0008	−0.089*	0.084**	0.050*	−0.046
	(0.092)	(0.056)	(0.036)	(0.029)	(0.033)
Previous occupation					
Low-level occupation	−0.316***	−0.121***	−0.115***	−0.115***	0.036***
	(0.024)	(0.014)	(0.009)	(0.008)	(0.008)
Other occupation	Ref.	Ref.	Ref.	Ref.	Ref.
High-level occupation	0.316***	0.049**	0.163***	0.179***	−0.076***
	(0.040)	(0.022)	(0.016)	(0.013)	(0.014)
Has never worked	−0.704***	−0.233***	−0.274***	−0.113***	−0.083***
	(0.035)	(0.019)	(0.013)	(0.011)	(0.013)
Foreigner (0/1)	−0.100***	−0.132***	0.0261**	−0.038***	0.044***
	(0.030)	(0.017)	(0.012)	(0.009)	(0.010)
Child (0/1)	−0.062***	−0.032*	0.022**	−0.019**	−0.033***
	(0.024)	(0.013)	(0.009)	(0.007)	(0.008)
Age					
15–29	0.036***	0.226***	0.020*	0.067***	0.045***
	(0.029)	(0.016)	(0.011)	(0.009)	(0.010)
30–39	0.072**	0.064***	0.008	0.002	−0.003
	(0.028)	(0.016)	(0.011)	(0.009)	(0.010)
40–49	Ref.	Ref.	Ref.	Ref.	Ref.
50–59	−0.300***	−0.128***	−0.007	−0.059***	−0.103***
	(0.030)	(0.017)	(0.012)	(0.010)	(0.011)
Above 60	−0.696***	−0.381***	−0.011	−0.111***	−0.191***
	(0.053)	(0.029)	(0.021)	(0.017)	(0.019)
Sex (female)	−0.137***	0.075***	−0.084***	0.027***	−0.156***
	(0.018)	(0.0104)	(0.007)	(0.006)	(0.007)
Partner's status					
Employed partner	0.063***	0.025*	0.039***	0.014*	−0.015*
	(0.024)	(0.013)	(0.009)	(0.007)	(0.008)
Unemployed partner	0.095*	0.044	0.025	0.009	0.018
	(0.053)	(0.029)	(0.021)	(0.017)	(0.019)
No partner	Ref.	Ref.	Ref.	Ref.	Ref.
Inactive partner	−0.191***	−0.125***	−0.013	−0.018*	−0.036***
	(0.033)	(0.018)	(0.013)	(0.011)	(0.012)
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	−96,644	−68,816	−52,423	−43,318	−48,132
N (Obs./ Sectors/ Clusters x t/ Indiv.)	49,696 / 2,882 / 31,346 / 33,735				

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents the full set of estimated coefficients in Equation 1, estimated on the main estimation sample. See Table B.1 and Table 3 for a detailed presentation of the independent variables.

Online appendix for

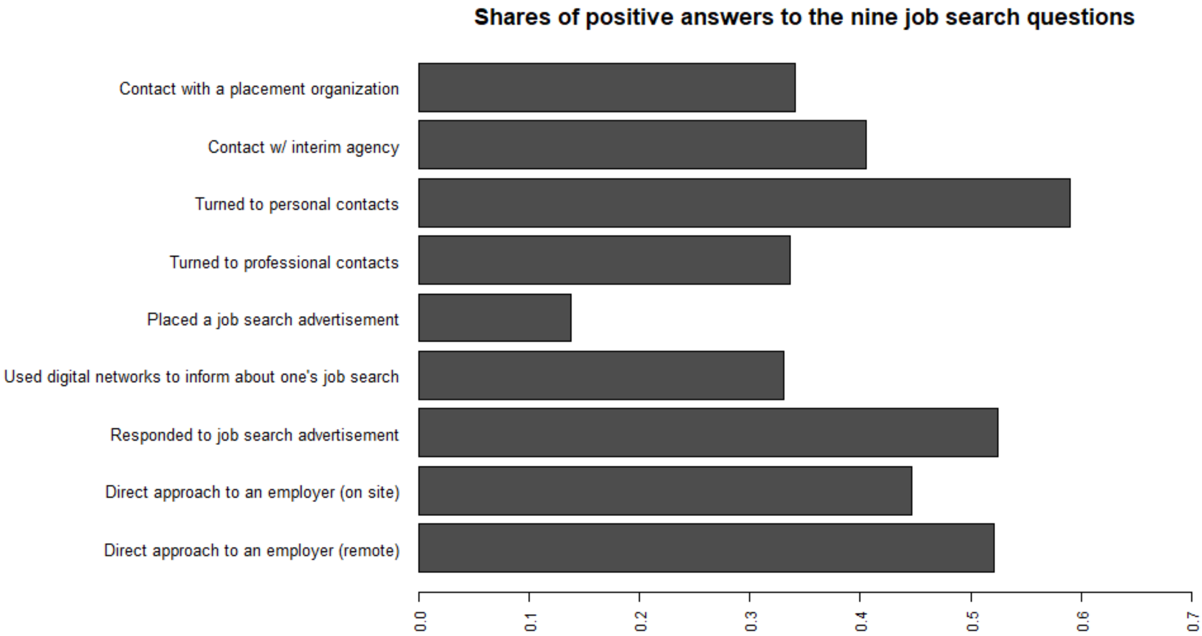
"Neighborhood effects and job search behaviors"

Florence Goffette-Nagot

Marie Aurélie Lapierre

D Basic statistics on original search behavior questions

Figure D.1: Share of positive answers to the nine search methods questions



Notes: This figure plots the share of positive answers to each of the nine FLFS questions used to build measures of JS behavior. The sample consists of 80,038 observations including all unemployment periods observed in FLFS 2014-2019, in large urban areas for individuals aged 15-64.

Table D.1: Tetrachoric correlations between the nine search methods questions

	Interim	Personal contacts	Professional contacts	Placed ad	Digital networks	Responded to an ad	Direct on site	Direct remote
Placement agency	0.133	0.031	0.036	0.072	0.061	0.090	0.062	0.076
Interim		0.083	0.070	0.107	0.120	0.256	0.170	0.208
Personal contacts			0.593	0.197	0.255	0.104	0.221	0.178
Professional contacts				0.220	0.304	0.147	0.193	0.185
Placed ad					0.479	0.292	0.260	0.393
Digital networks						0.315	0.204	0.387
Responded to ad							0.341	0.529
Direct on site								0.544
Estimation sample	80,038 obs. / 3,078 sectors / 38,898 cluster x quarter / 39,872 indiv.							

Notes: The sample consists of 80,038 observations including all unemployment periods observed in FLFS 2014-2019, in large urban areas for individuals aged 15-64.

Table D.2: List of excluded questions

- Have you done some missions with a temporary employment agency (interim)?
- Have you had a test or an interview for a job?
- Did you take part in an entry test for civil service?
- Have you been to a professional fair or a job forum?
- Have you reviewed some job advertisements?
- Have you tried to take over a company, a business or an established practice?
- Have you been looking for land, premises or equipment?
- Did you seek financial resources (bank loans, public grants, etc.)?
- Have you applied for a permit, a licence or an authorisation to set up a business?
- Have you been waiting for the results of previous attempts/procedures (test, Interviews, etc.)?
- Have you been waiting for a call from Pôle Emploi, a placement operator or a job placement association?
- Have you been waiting for the result of an entry test for civil service?

E Alternative measures of JS behavior

Figure E.1: Linear probability model of getting a job - 9 item questions included in total search

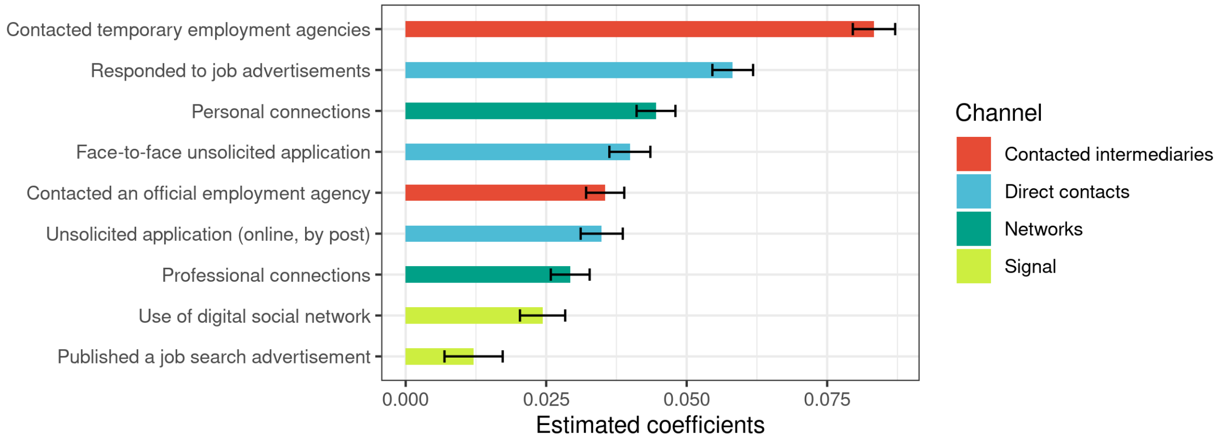


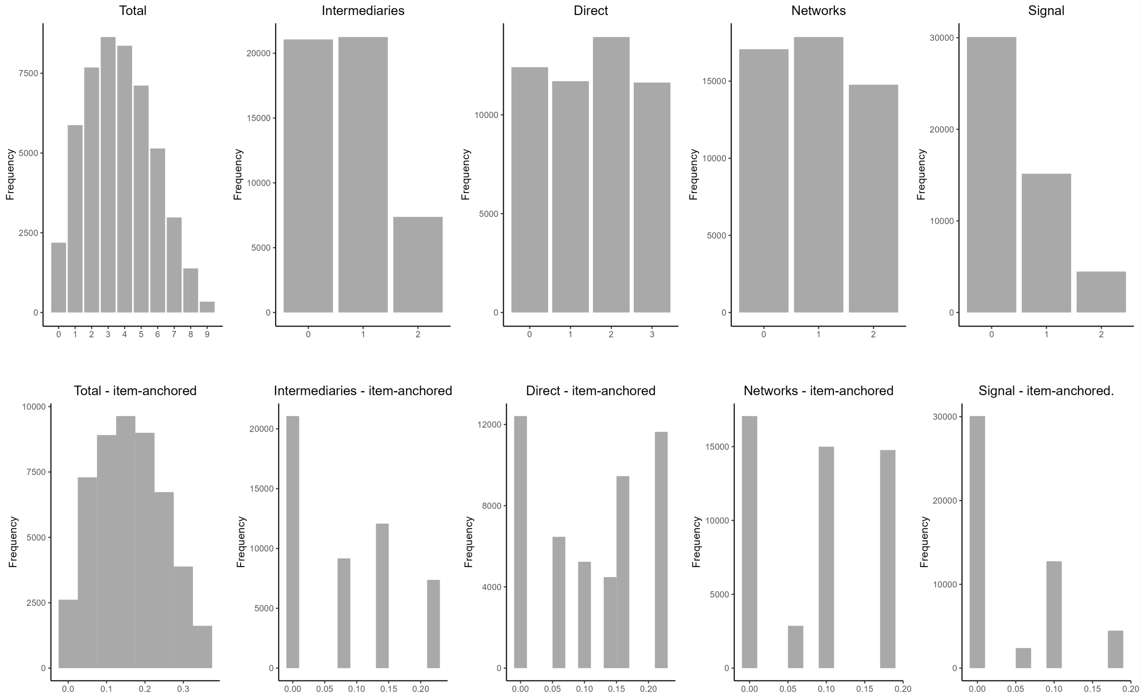
Table E.1: Linear probability model of getting a job - estimated coefficients

	Dependent variable: getting a job in $t+1$				
	Total	Direct	Networks	Signal	Interm.
	(1)	(3)	(4)	(5)	(2)
Face-to-face unsolicited application	0.040***	0.067***			
	(0.004)	(0.004)			
Unsolicited application (online, by post)	0.035***	0.067***			
	(0.004)	(0.004)			
Responded to job advertisements	0.058***	0.093***			
	(0.004)	(0.004)			
Personal connections	0.045***		0.108***		
	(0.003)		(0.003)		
Professional connections	0.029***		0.063***		
	(0.004)		(0.004)		
Use of digital social networks	0.024***			0.107***	
	(0.004)			(0.004)	
Published a job search advertisement	0.012***			0.069***	
	(0.005)			(0.005)	
Contacted an official employment agency	0.035***				0.071***
	(0.003)				(0.003)
Contacted temporary employment agencies	0.083***				0.147***
	(0.004)				(0.004)
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Observations	90,877	90,877	90,877	90,877	90,877
Individuals	31,537	31,537	31,537	31,537	31,537
R^2	0.513	0.501	0.493	0.484	0.495
Adjusted R^2	0.253	0.236	0.223	0.209	0.227

*p<0.1; **p<0.05; ***p<0.01

Notes: The sample includes all periods in employment or unemployment for individuals unemployed at least in one quarter in FLSL 2014-2019, restricted to large urban areas and individuals aged 15-64.

Figure E.2: Distribution of the main and item-anchored job search variables



F Heterogeneity analysis

Table F.2: Regression results for three density subsamples

	Explained variable				
	Total	Direct	Network	Signal	Interm.
	(1)	(2)	(3)	(4)	(5)
Panel A: Dense sectors					
Endogenous effects					
Un. neighbors' average intensity	0.105***	0.085***	0.121***	0.100***	0.074***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Has unemp. neighbor (0/1)	−0.406***	−0.146***	−0.095***	−0.067***	−0.067***
	(0.057)	(0.032)	(0.022)	(0.019)	(0.020)
Group effects *(among non-unemp. neighb.)*					
% employed	0.036	−0.0004	0.099*	−0.047	−0.016
	(0.134)	(0.007)	(0.052)	(0.043)	(0.047)
% low-level occupations	−0.180	−0.044	−0.093**	−0.054	0.013
	(0.117)	(0.063)	(0.045)	(0.037)	(0.041)
% high-level occupations	−0.287*	−0.152*	−0.024	−0.022	−0.142***
	(0.150)	(0.082)	(0.058)	(0.048)	(0.053)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	0.0002	0.003	−0.011	0.019	−0.007
	(0.062)	(0.034)	(0.024)	(0.020)	(0.022)
% has never worked	0.053	0.034	0.011	0.005	0.005
	(0.081)	(0.044)	(0.032)	(0.026)	(0.029)
Indiv. characteristics	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	−27,917	−19,757	−15,094	−12,207	−13,865
N (Obs./ Sectors/ Clusters x t/ Indiv.)	14,389 / 820 / 8,386 / 10,172				
Dependent variable mean	3.60	1.47	1.00	0.51	0.70
Dependent variable s.d.	2.05	1.10	0.81	0.66	0.70
Panel B: Mixed sectors					
Endogenous effects					
Un. neighbors' average intensity	0.070***	0.059***	0.078***	0.088***	0.048***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Has unemp. neighbor (0/1)	−0.283***	−0.092***	−0.058***	−0.073***	−0.045**
	(0.050)	(0.028)	(0.020)	(0.017)	(0.018)
Group effects *(among non-unemp. neighb.)*					
% employed	−0.015	0.095	−0.046	−0.029	−0.033
	(0.130)	(0.072)	(0.051)	(0.042)	(0.047)
% low-level occupations	−0.252**	−0.155**	−0.009	−0.098***	0.009
	(0.106)	(0.058)	(0.041)	(0.034)	(0.038)
% high-level occupations	0.132	−0.067	0.149**	0.026	0.022
	(0.155)	(0.086)	(0.061)	(0.049)	(0.055)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	−0.010	−0.031	−0.003	0.018	0.009
	(0.056)	(0.031)	(0.022)	(0.018)	(0.020)
% has never worked	0.115	0.058	−0.004	0.045	0.019
	(0.076)	(0.042)	(0.030)	(0.025)	(0.027)
Indiv. characteristics	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	−33,441	−23,851	−18,208	−14,960	−16,717
N (Obs./ Sectors/ Clusters x t/ Indiv.)	17,155 / 942 / 10,635 / 11,722				
Dependent variable mean	3.66	1.51	0.94	0.47	0.75
Dependent variable s.d.	2.02	1.09	0.79	0.65	0.71

	Explained variable				
	Total	Direct	Network	Signal	Interm.
	(1)	(2)	(3)	(4)	(5)
<u>Panel C: Non-dense sectors</u>					
Endogenous effects					
Un. neighbors' average intensity	0.064***	0.072***	0.063***	0.084***	0.047***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Has unemp. neighbor (0/1)	−0.245***	−0.084***	−0.068***	−0.049***	−0.057***
	(0.050)	(0.028)	(0.019)	(0.016)	(0.018)
Group effects *(among non-unemp. neighb.)*					
% employed	0.061	0.050	0.011	0.010	−0.013
	(0.147)	(0.081)	(0.056)	(0.047)	(0.051)
% low-level occupations	−0.094	−0.124*	−0.011	0.002	0.041
	(0.123)	(0.068)	(0.047)	(0.039)	(0.043)
% high-level occupations	0.228	−0.018	0.076	0.174**	−0.005
	(0.181)	(0.100)	(0.070)	(0.058)	(0.064)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	−0.034	−0.042	0.007	−0.003	0.008
	(0.054)	(0.030)	(0.021)	(0.017)	(0.019)
% has never worked	0.071	0.051	0.021	−0.102	0.003
	(0.073)	(0.041)	(0.028)	(0.019)	(0.026)
Indiv. characteristics	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	−35,218	−25,149	−19,063	−15,733	−17,480
N (Obs./ Sectors/ Clusters x t/ Indiv.)	18,152 / 1,120 / 12,325 / 11,841				
Dependent variable mean	3.66	1.51	0.93	0.48	0.72
Dependent variable s.d.	2.05	1.11	0.79	0.65	0.71

*p<0.1; **p<0.05; ***p<0.01

Note: See Table 3 for a detailed presentation of the independent variables.

Table F.2: Regression results for periods 2014-2016 and 2017-2019

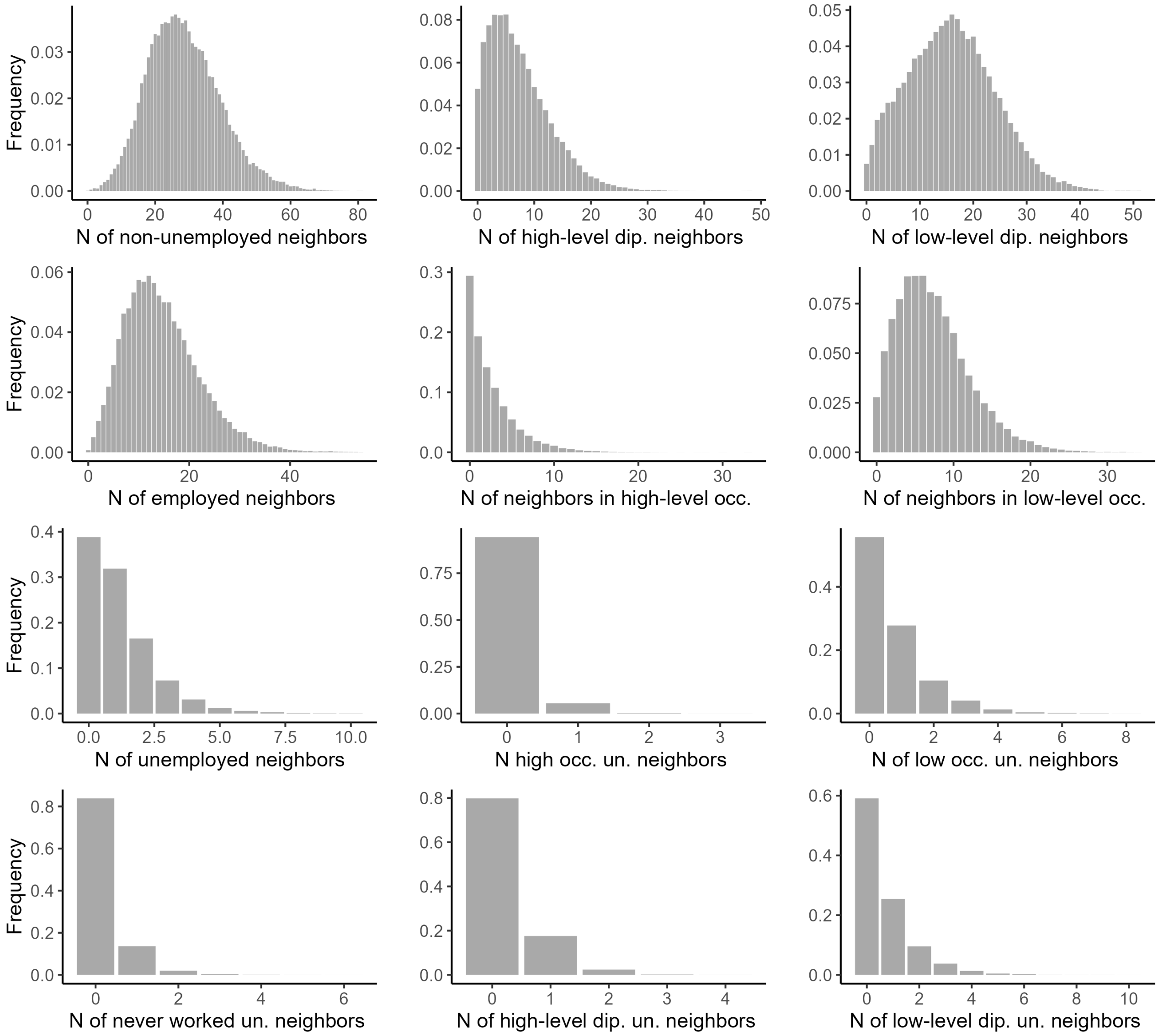
	Explained variable				
	Total	Direct	Network	Signal	Interm.
	(1)	(2)	(3)	(4)	(5)
Panel A: Period 2014 to 2016					
Endogenous effects					
Un. neighbors' average intensity	0.095***	0.080***	0.107***	0.109***	0.070***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	−0.037	−0.045*	−0.004	0.007	0.009
	(0.046)	(0.025)	(0.018)	(0.015)	(0.017)
% has never worked	0.053	0.024	0.014	0.015	0.002
	(0.062)	(0.034)	(0.024)	(0.020)	(0.022)
Has unemp. neighbor (0/1)	−0.367***	−0.123***	−0.078***	−0.069	−0.075***
	(0.043)	(0.023)	(0.016)	(0.014)	(0.015)
Group effects *(among non-unemp. neighb.)*					
% employed	−0.171	−0.032	−0.058	−0.056	−0.023
	(0.122)	(0.067)	(0.047)	(0.039)	(0.043)
% low-level occupations	−0.218**	−0.089	−0.028	−0.064*	−0.035
	(0.103)	(0.056)	(0.040)	(0.033)	(0.036)
% high-level occupations	−0.228	−0.138*	−0.057	0.061	−0.095*
	(0.145)	(0.079)	(0.056)	(0.047)	(0.051)
Log-likelihood	−49,283	−34,925	−26,597	−22,265	−24,596
N (Obs./ Sectors/ Clusters x t/ Indiv.)	26,604 / 2,623 / 16,267 / 18,786				
Dependent variable mean	3.74	1.53	0.98	0.49	0.74
Dependent variable s.d.	2.05	1.09	0.79	0.67	0.71
Panel B: Period 2017 to 2019					
Endogenous effects					
Un. neighbors' average intensity	0.115***	0.129***	0.125***	0.124***	0.113***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Contextual effects *(among unemp. neighb.)*					
% ex-low-level occupations	0.038	0.014	0.021	0.018	−0.009
	(0.052)	(0.029)	(0.020)	(0.016)	(0.018)
% has never worked	0.162**	0.101***	0.042	0.014	0.008
	(0.069)	(0.038)	(0.027)	(0.021)	(0.024)
Has unemp. neighbor (0/1)	−0.471***	−0.213***	−0.126***	−0.078***	−0.090***
	(0.048)	(0.026)	(0.019)	(0.015)	(0.017)
Group effects *(among non-unemp. neighb.)*					
% employed	0.006	0.037	0.039	−0.020	−0.051
	(0.135)	(0.075)	(0.052)	(0.043)	(0.048)
% low-level occupations	−0.085	−0.090	−0.047	−0.037	0.091**
	(0.109)	(0.061)	(0.042)	(0.034)	(0.039)
% high-level occupations	0.017	−0.057	0.106*	−0.025	−0.005
	(0.155)	(0.086)	(0.061)	(0.048)	(0.055)
Log-likelihood	−41,203	−29,427	−22,185	−17,822	−20,325
N (Obs./ Sectors/ Clusters x t/ Indiv.)	23,092 / 2,838 / 15,079 / 16,118				
Dependent variable mean	3.57	1.46	0.93	0.48	0.70
Dependent variable s.d.	2.03	1.11	0.80	0.64	0.70
In both panels					
Indiv. characteristics	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Notes: Table F.2 presents estimation of the main model on a sample restricted to 2014-2016 (Panel A) and on a sample restricted to 2017-2019 (Panel B). See Table 3 for a detailed presentation of the independent variables.

G Distribution of neighbors by characteristics in the estimation sample

Figure G.1: Number of neighbors by characteristics in the estimation sample



Notes: Figure G.1 displays the distribution of neighbors by characteristics in the estimation sample. The first row presents the distribution of the number of non-unemployed neighbors and among them, how many have high-level or low-level diplomas. The second row present the number of employed neighbors, the number of employed neighbors in high-level occupations and the number of employed neighbors in low-level occupations. The third and fourth rows present the number of unemployed neighbors, their previous occupations and level of diploma. For the definition of occupations and diplomas, see Table B.1.

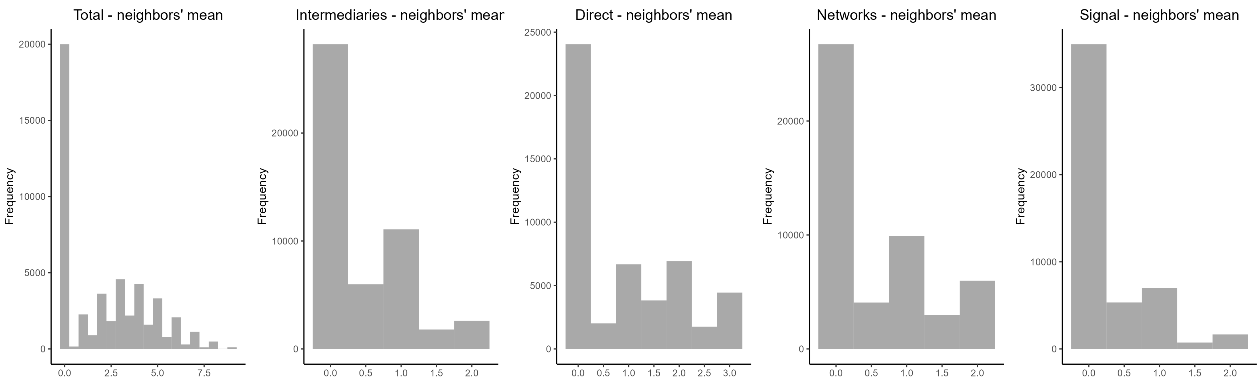
H Distribution of endogenous, contextual and group effects

Table H.1: Distribution of endogenous, contextual and group effect variables

	Min	Q1	Median	Q3	Max	Mean	SD
Endogenous effects: *Unemp. neighbors' average intensity*							
Total	0	0	2	4	9	2.216	2.247
Direct	0	0	0.500	2	3	0.910	1.041
Network	0	0	0	1	2	0.575	0.714
Signal	0	0	0	0.500	2	0.286	0.504
Interm.	0	0	0	1	2	0.446	0.591
Contextual effects: *Shares among unemployed neighbors*							
% low-level occupations	0	0	0	1	1	0.368	0.441
% high-level occupations	0	0	0	0	1	0.039	0.176
% have never worked	0	0	0	0	1	0.099	0.255
Group effects							
Shares among non-unemployed neighbors							
% employed	0	0.400	0.510	0.611	1	0.506	0.156
Shares among employed neighbors							
% low-level occupations	0	0.333	0.519	0.700	1	0.520	0.247
% high-level occupations	0	0	0.111	0.250	1	0.166	0.182
Estimation sample	49,696 obs. / 2,882 sectors / 31,346 cluster x quarter / 33,735 indiv.						

Notes: This table presents indicators of the distribution of endogenous, contextual and group effects on the estimation sample, as defined in the text. Neighbors are individuals surveyed in the same cluster × quarter as the sampled individual, excluding herself in endogenous effects, and her household members in endogenous, contextual and group effects.

Figure H.1: Histograms of endogenous variables on the estimation sample



Notes: This figure present plots of the distributions of endogenous variables (exclusive neighbors' averages) on the estimation sample.

I Characteristics of unemployed on different samples

Table I.1: Descriptive statistics: individual alone vs. not alone

	Alone %	Not alone %
Age		
Age 15+	37.2	38.0
Age 30+	20.9	22.5
Age 40+	19.4	19.5
Age 50+	18.7	16.7
Age 60+	3.8	3.3
Female	48.6	48.6
Has one child or more	35.4	38.7
Nationality		
French	90.1	86.7
Foreigner	9.9	13.3
Education [a]		
Low-level diploma	47.1	54.4
Baccalaureate	22.3	21.7
High-level diploma	30.1	23.5
Missing	0.5	0.5
Previous occupation [a]		
Farmers	0.1	0.1
Independent workers	2.9	2.8
High-level occupations	9.4	6.5
Intermediate occupations	16.8	13.5
Low-level occupations	54.6	59.7
Unemployed (have never worked)	15.3	16.8
Missing	0.9	0.7
Partner's employment status[a]		
Employed partner	33.0	29.2
Unemployed partner	2.9	3.7
Inactive partner	9.5	11.2
No partner	54.6	55.9
Missing	0.0	0.0
Dwelling's architectural environment		
Scattered houses outside of urban agglomerations	9.9	7.3
Houses in an urban or sub-urban environment	36.7	30.2
Flats in high-rise housing projects	9.3	18.6
Other flats in urban areas	25.7	24.5
Mixed housing	4.7	5.2
Missing	13.7	14.2
Type of area[b]		
Rural municipalities[b]	17.0	13.1
Urb. unit less than 10,000 inhabitants	8.9	7.5
Urb. unit 10,000 to 50,000 inhabitants	9.7	10.1
Urb. unit 50,000 to 100,000 inhabitants	8.9	9.1
Urb.unit 100,000 to 200,000 inhabitants	6.2	7.8
Urb. unit more than 200,000 inhab. (except Paris)	30.3	34.5
Paris urban unit	19.0	17.8
N individuals	13,131	26,029
N obs.	19,297	30,399

Notes: This table shows the characteristics of unemployed present on two sub-samples derived from the main sample. The first sample includes all individuals who have been without unemployed neighbors at some point within the 6 quarters of observation. The second one comprises all individuals who have had unemployed neighbors at some point within the 6 quarters of observation. 5,425 individuals are obserced at different dates with no unemployed neighbors, and with unemployed neighbors. [a] For a definition of education and occupations, see Table B.1. [b] Rural municipalities in the sample are municipalities below 2000 inhabitants part of an urban area. See note 2 for the definition of urban areas.

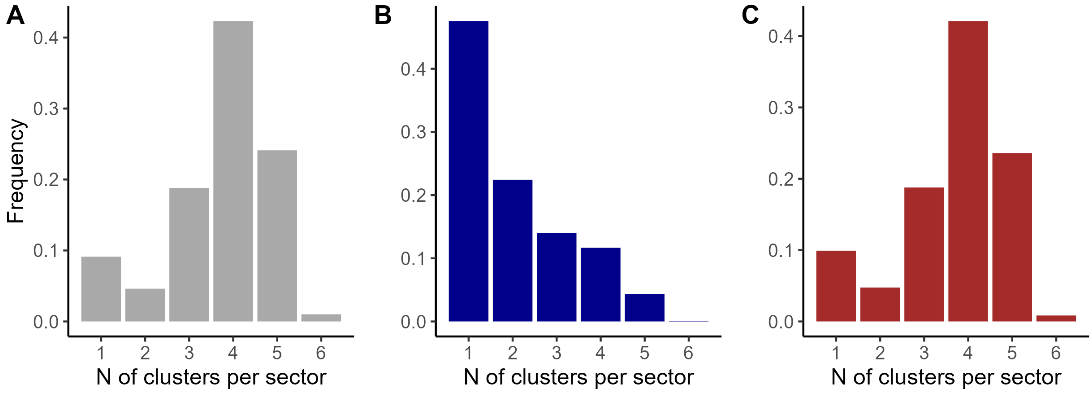
Table I.2: Descriptive statistics (in %) on different samples

	Main sample A	W/o pub hsg B	W/o heterog. C	By sector density: Dense D	Mixed E	Non dense F
Age						
Age 15+	38.9	39.4	38.9	37.8	39.2	39.0
Age 30+	22.1	21.2	22.1	24.2	22.6	19.8
Age 40+	19.1	18.4	19.0	19.8	19.0	18.6
Age 50+	16.6	17.1	16.7	15.2	15.9	18.7
Age 60+	3.3	3.9	3.4	3.1	3.3	3.9
Female	48.9	49.3	49.2	47.3	48.8	50.4
Has one child or more	37.8	34.5	37.0	37.9	37.1	38.3
Nationality						
French	87.6	91.0	88.5	77.8	87.8	95.9
Foreigner	12.4	9.0	11.5	22.2	12.2	4.1
Education[a]						
Low-level diploma	52.1	45.5	50.1	50.5	53.6	51.9
Baccalaureate	22.1	23.6	22.4	20.4	21.0	24.5
High-level diploma	25.3	30.4	27.0	28.4	24.8	23.2
Missing	0.5	0.5	0.5	0.7	0.6	0.5
Previous occupation[a]						
Farmers	0.1	0.1	0.1	0.0	0.1	0.1
Independent workers	2.9	3.2	2.9	2.9	2.7	2.9
High-level occupations	7.2	9.3	7.9	8.8	6.5	6.5
Intermediate occupations	14.3	16.8	15.2	13.3	14.6	15.1
Low-level occupations	57.8	54.0	56.4	56.3	59.4	58.1
Unemployed (have never worked)	17.0	15.8	16.7	17.8	16.0	16.6
Missing	0.7	0.8	0.7	0.9	0.8	0.7
Partner's employment status[a]						
Employed partner	30.3	34.4	31.5	25.3	28.1	36.7
Unemployed partner	3.6	3.1	3.5	4.0	3.7	3.0
Inactive partner	10.7	9.2	9.9	12.0	10.8	9.8
No partner	55.4	53.2	55.1	58.8	57.4	50.5
Missing	0.0	0.0	0.0	0.0	0.0	0.0
Dwelling's architectural environment						
Scattered houses outside of urb. agglo.	8.0	11.5	14.8	0.5	2.7	19.8
Houses in an urb. or suburb. envir.	31.6	39.5	8.6	1.7	27.2	61.7
Flats in high-rise housing projects	16.1	3.9	33.0	35.5	14.9	0.5
Other flats in urban areas	24.6	24.9	25.5	45.2	27.3	4.3
Mixed housing	5.0	4.7	13.1	0.6	12.7	1.1
Missing	14.7	15.5	5.1	16.5	15.2	12.7
Type of area[b]						
Rural municipalities[b]	14.1	19.7	15.1	0.0	3.0	37.3
Urb. unit less than 10,000 inhab.	7.8	9.6	8.2	0.4	7.7	14.1
Urb. unit 10,000 to 50,000 inhab.	10.1	9.5	9.9	4.4	14.5	10.5
Urb. unit 50,000 to 100,000 inhab.	9.1	7.7	8.2	8.9	11.1	7.2
Urb.unit 100,000 to 200,000 inhab.	7.4	6.1	7.0	7.5	10.5	4.4
> than 200,000 inhab. (except Paris)	33.3	32.2	33.1	41.9	37.2	22.2
Paris urban unit	18.2	15.3	18.4	36.8	16.0	4.4
N individuals	33,735	20,514	29,455	10,172	11,722	11,841
N obs.	49,696	31,427	43,848	14,389	17,155	18,152

Table I.2 shows the characteristics of unemployed present on six different samples: *A* the estimation sample; *B* discards social housing clusters; *C* removes heterogeneous sectors in terms of % high-level occupations; *D* comprises dense sectors; *E* is made of mixed sectors and *F* keeps non-dense sectors. [a] See Table B.1 for variables definitions. [b] Rural municipalities in the sample are municipalities below 2000 inhabitants part of an urban area. See note 2 for the definition of urban areas.

J Distribution of the number of clusters per sector and the number of individuals by characteristics

Figure J.1: Distribution of the number of clusters per sector



The above figure shows the distribution of the number of clusters per sector in: A = the estimation sample, B = the sample discarding public housing clusters and C = the sample removing heterogenous sectors.

Table J.1: Number of individuals by characteristics in the clusters x quarter - Main estimation sample

	Min	Q1	Median	Q3	Max	Mean	SD
# individuals	2	24	31	39	85	31.464	11.117
# unemployed	1	1	1	2	11	1.585	0.930
# unemp. low occupations	0	0	1	1	8	0.919	0.889
# unemp. high occupations	0	0	0	0	3	0.126	0.350
# unemp. never worked	0	0	0	0	6	0.244	0.500
# non-unemployed	1	22	29	37	83	29.583	11.006
# employed	1	10	14	20	55	15.271	7.590
# employed low occupations	0	4	7	10	34	7.315	4.796
# employed high occupations	0	1	2	4	34	2.818	3.070
N cluster x quarter				31,346			

Notes: This table describes the distribution of the number of all, unemployed, non-unemployed, and employed individuals by characteristics for the 31,346 clusters x quarter present in the estimation sample. They contribute to the understanding of how the different groups used to compute the endogenous, group and contextual effects vary in terms of size. For the definition of occupations and diplomas, see Table B.1.