Neighborhood effects and job search behaviors

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Abstract

This paper aims to test for the influence of interactions with neighbors on job search behaviors of unemployed individuals. Using data from the 2014-2019 French Labor Force Survey, we implement a model of endogenous, contextual and group effects inspired from Manski (1993) and applied to job search intensity for different channels. We control for location endogeneity in a similar way as in Bayer et al. (2008) and tackle the reflection issue by using the approach proposed by Lee (2007) and developed by Boucher et al. (2014). We find evidence of endogenous peer effects for all the job search channels, which indicates the existence of imitation or spread of information effects, particularly for job search through personal and professional networks. We also find some contextual and group effects with regards to neighbors' occupations. Such results underline the importance for job search of being surrounded by neighbors with strong labor market connections, and suggest that local social interaction effects in job search could amplify labor market inequalities across neighborhoods.

JEL classification: J21, J64, R23.

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

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1 Introduction

Several studies have shown the importance of interactions with neighbors for labor market outcomes. In particular, this literature stresses the role of contacts with employed neighbors, especially in high positions, in access to information on job opportunities and in creation of networks that facilitate employment (Bayer et al., 2008; Hellerstein et al., 2011, 2014; Schmutte, 2015; see Topa and Zenou, 2015, for a survey). The neighborhood effects literature also underlines the existence of peer effects in behaviors such as attitudes towards work (Wilson, 1987; Crane, 1991; Cutler and Glaeser, 1997) or human capital acquisition (Benabou, 1993; Evans et al., 1992; Goux and Maurin, 2007; Del Bello et al., 2015).

Another body of literature underlines the influence of job search on labor market outcomes (Mortensen and Pissarides, 1999; Pissarides, 2000; Zenou, 2009) and shows that the use of different job search channels (formal vs. informal methods) induces different equilibria in terms of unemployment duration and job quality (Holzer, 1988; Böheim and Taylor, 2001; Addison and Portugal, 2002; Merlino, 2014; Stupnytska and Zaharieva, 2015). A particular attention has been brought to job search through networks, pointing out its higher efficiency (Granovetter, 1995; Caliendo et al., 2015; Cingano and Rosolia, 2012; Jackson et al., 2020).

Overall, while the literature reveals the presence of neighborhood effects in finding job opportunities and in producing good and efficient matches on the labor market, job search behaviors have not really been considered as such in this literature, which contrasts with their importance in labor economics. There has also been very few papers targeting job search behaviors in the analysis of spatial unemployment inequalities. Among exceptions are Patacchini and Zenou (2005, 2006), who estimate how the local share of actively searching individuals among job-seekers is affected by access to jobs, transportation modes, local labor market constraints and costs of living. Our paper aims to fill these gaps by shedding light on the presence of neighborhood effects at the pre-hiring stage, with an analysis of job search behaviors.

The French Labor Force Survey (*Enquête Emploi*, FLFS in the following) from the INSEE (French National Institute for Statistics and Economic Studies) enables us to build measures of job search intensity at the individual level, distinguishing three job search channels, namely search through employment organizations, search through active and direct actions, and search through personal and professional networks. It also allows us to identify two nested levels of neighborhoods at a very fine level, with clusters of 20 contiguous dwellings, where daily interactions between residents can be assumed, grouped into larger neighborhoods.

We frame these social interactions questions in a model à la Manski (1993) of endogenous (how the average behavior of neighbors impacts individual behavior), contextual and group effects (how neighbors' characteristics impact individual behavior) applied to job search through three channels and to total search intensity. Two identification issues have to be thoroughly considered for the consistent estimation of social interaction effects. First, one has to deal with correlated effects that are likely to bias the estimation of interaction effects. Second, linear-in-means models are affected by a perfect collinearity between the group mean characteristics and the average behavior, which requires specific identification strategies to disentangle endogenous effects and contextual effects. We tackle this reflection issue by applying Lee (2007)'s strategy which uses exclusive averaging and exploits group size variations. As to the the non-random sorting of individuals into neighborhoods, we follow Bayer et al. (2008) and assume that location within neighborhoods (clusters) can be considered as exogenous conditional on a larger neighborhood level (groups of contiguous clusters).

Our results suggest the existence of neighborhood effects in job search behavior. We find important endogenous effects for the three job search channels considered and for total search intensity. The higher the search intensity of unemployed peers through a particular channel, the higher the individual's job search intensity through the same channel. These effects are particularly important for search through networks. These endogenous effects could be explained by a word-of-mouth learning process through which unemployed neighbors give each other tips and advice, thus reducing job search costs, or by social pressure that creates a need to conform to the job search behavior promoted within the neighborhood. We also find some contextual and group effects. A higher proportion of employed neighbors favors search through networks, and the underlying mechanisms are thought to be both perceptions of neighborhood unemployment status and access to information about job opportunities. Our results also draw attention to the role of neighbors' occupations. The higher the share of low-level occupations of neighbors, the lower the overall search intensity, the active and direct search, and the search through networks. The effect is more important for search through networks, for which we also find a positive impact of the share of high-level occupation neighbors. Since occupation reflects position in the labor market, these results underscore the importance of being surrounded by neighbors with strong labor market connections who create a more conducive environment for job search. These results are robust to a number of complementary analyses involving alternative measures of search intensity or endogenous effects, the inclusion of a network formation model, and subsample specifications that remove public housing clusters and heterogeneous sectors. Moreover, estimations on two subsamples with different density of architectural environment reveal that these neighborhood effects on job search behaviors are stronger in denser areas, which goes against the conventional wisdom that neighborly relations are non-existent in high-rise neighborhoods.

Our contribution to the literature is threefold. First, we participate in the literature on job search behaviors with the use of detailed data that allows us to precisely investigate the job search intensity for different channels used by unemployed. Second, we add to the literature on neighborhood effects in labor market outcomes by analyzing job search behaviors, thus focusing on the pre-hiring stage. Third, this paper constitutes one of the first empirical applications of the social interactions' identification strategy proposed by Lee (2007) and developed by Boucher et al. (2014).[1]

The remainder of the paper is organized as follows. Section 2 places this paper in the context of the literature on job search behavior and the broader literature on neighborhood effects on labor market outcomes. Section 3 describes the French Labor Force Survey, presents the estimation sample and some descriptive statistics. Section 4 exposes the empirical design and the methods used to address the reflection and the location endogeneity issues. We present the empirical findings in Section 5, provide some robustness checks in Section 6, discuss the results in Section 7 and conclude in Section 8.

2 Related literature

The literature regarding job search behaviors shows that some job search channels are more effective than others, involve different costs, are more or less accessible, and might therefore influence search effort through anticipation effects (Holzer, 1988; Granovetter, 1995; Addison and Portugal, 2002; Böheim and Taylor, 2001; Carroll and Tani, 2015). A particular attention has been brought to job search through networks, underlining its importance in finding a job (Cingano and Rosolia, 2012; Zenou, 2015; Jackson et al., 2020) and in job quality (Montgomery,

[1] To the best of our knowledge, the only other empirical work that takes advantage of group size variation with exclusive averaging to identify peer effects as in Boucher et al. (2014) is Izaguirre and Di Capua (2020).

1991; Caliendo et al., 2015), while the structure of social ties has been shown to create labor market inequalities across individuals (Calvó-Armengol and Jackson, 2004, 2007; Jackson et al., 2017). Individual determinants and household characteristics affect the use of job search channels. Results are however mixed. Some papers show that informal networks are more likely to be used by less-privileged individuals (Ioannides and Loury, 2004; Vázquez-Grenno, 2018), while others state that highly-educated tend to rely more on their network (Bachmann and Baumgarten, 2013; Piercy and Lee, 2019). Patacchini and Zenou (2005) stress the importance of location on search intensity, which decreases with higher commuting times and distance to the city centre. They hypothesize that this result is due to higher costs of gathering information on job opportunities and to anticipation effects on future high commuting costs. Patacchini and Zenou (2006) also underline the influence of local labor market constraints and local costs of living on search intensity. Higher local labor market tightness, that is more job vacancies, fosters search activities, as the prospect of leaving unemployment increases, while higher costs of living increase the expected lifetime differences between employment and unemployment.

Wilson (1987) is one of the first to argue that interactions with neighbors are important in understanding the persistence of inner city poverty, because they are likely to affect human capital acquisition process, attitudes towards work or access to information on job opportunities. Several studies have indeed shown how living in neighborhoods of low socioeconomic status (Andersson, 2004; Dujardin et al., 2008; Alivon and Guillain, 2018; Eilers et al., 2021) or how local employment shifts (Topa, 2001; Jahn and Neugart, 2020) affect employment probability. With a similar rationale, other studies have focused on the role played by networks within neighborhoods, and emphasized the importance of residential local networks (see a survey in Topa and Zenou, 2015). Bayer et al. (2008) find, using US Census data, that residing in the same versus nearby blocks increases the probability of working in the same firm by 33%. Hellerstein et al. (2011) find similar evidence by capturing the importance of local market networks through the disproportionate non-random presence of co-residents in a worker's own firm. Building on the strategy developed in Bayer et al. (2008), Hémet and Malgouyres (2019) show, using the FLFS, that similar patterns exist in the French case, with local neighborhood referral networks particularly important for out-of-unemployment transitions. Hellerstein et al. (2014) study the productivity of residential local networks and find that they have significant effects in reducing turnover and increasing earnings. Analogous results are found in Schmutte (2015), who shows that local high-quality referrals favor high-ability workers matches in high-paying firms, as neighbors with high-quality jobs can provide direct referrals to employers, share information about local job opportunities, or on pay differentials across firms around the neighborhood. These phenomena have also been studied by sociologists, as for instance in the recent survey *"Mon quartier, mes voisins"* (My neighborhood, my neighbors), which shows that neighborhood relationships remain at high levels in France, that they are more frequent at the level of the building than the neighborhood, and that they can play a role in job search via exchanges of information on job opportunities (Bonneval, 2021; Authier and Cayouette-Remblière, 2021).

3 Data and descriptive statistics

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

3.1 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, with, for each of their members above 15, the status on the labor market, the characteristics of the main job held, the level of education, and the labor market trajectory. Each quarter, the FLFS sample comprises about 67,000 dwellings and 108,000 individuals. The FLFS definition of activity status is in line with the *International Labour Organisation* guidelines: it refers to a respondent's activity status during a specific period, namely a given *reference week*. Are considered unemployed, persons of working age (15 or over) who meet three conditions simultaneously: (i) being without employment during the 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.

The FLFS is a panel of dwellings, each surveyed for a period of six consecutive quarters. In each wave, the FLFS sample consists of 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, 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.[2] 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.[3] Consequently, individuals surveyed in the same cluster 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.

Moreover, as clusters are aggregated into sectors, the FLFS provides two nested levels of neighborhoods. We observe individuals living in very close clusters within the same sector, which is, as will be explained in Section 4, a key to the identification of neighborhood effects in our analysis.[4] However, given that the clusters in a sector are included in the FLFS sample in a row, individuals in different clusters in a sector are not surveyed at the same time.

As we observe very little on-the-job search in our data, with only 3.7% of employed individuals who search for another job, as compared with 94.5% among unemployed individuals, we restrict the analysis of job search behaviors to unemployed individuals, aged 15 or more. We restrict the analysis to large urban areas in mainland France.[5] We drop 23 individuals who are the only unemployed individual in a sector and also remove unemployed individuals who do not search because they have found a job that starts later or because they are seasonal workers observed in

[2]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.

[3]Figure A.2 in Appendix presents the example of a cluster of 23 dwellings in a rural community.

[4]As mentioned by the service in charge of the FLFS production: "*By the mere construction of the sample, the six clusters of the same sector are very close geographically: this may be within the same road or even in some cases within the same building in urban areas*". We have however no access to the exact location of clusters within sectors.

[5] 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.

a dead period. This yields an estimation sample of 26,427 individuals, each observed unemployed from 1 to 6 quarters, with a total of 56,602 observations.[6] This sample comprises 2,621 sectors (large neighborhoods) and 7,741 clusters (small neighborhoods). The total number of clusters $\times$ quarter is 30,873. As the empirical analysis in this paper covers a twenty-four quarters period, from Q1 of 2014 to Q4 of 2019, we can observe a maximum of four clusters in the same sector. As shown in Figure I.1 in Appendix, about half of the sectors in the estimation sample comprise three clusters, one fourth include four clusters, while the others have two clusters and a few ones only one.

Table 1 and table 2 present the variable definitions and Table 3 some descriptive statistics for the estimation sample. This sample is representative of the unemployed individuals in urban areas in France. There is a very high proportion of youths in the sample: 39% are aged between 15 and 29. Indeed, the share of youths among the unemployed has increased in recent years in France (Céreq, 2012). Consistently, our sample comprises 17.6% of new entrants on the labor market, who have never worked before. 14.2% of the unemployed were previously in intermediate occupations, 6.9% in high-level occupations (senior executives and higher intellectual occupations), while the majority were in low-level occupations (either blue-collar workers or low-level white-collars) before losing their jobs. Half of the sampled individuals hold low-level diplomas (vocational diploma or below). As we focus on large urban areas, two thirds of the sample live in urban units with more than 50,000 inhabitants, and half in urban units with more than 200,000 inhabitants. In terms of density of the urban fabric (proxied by dwellings' architectural environments), 48.3% of the individuals live in multifamily buildings in cities, among which 20.3% in high-rise housing projects usually more present in deprived neighborhoods. A third live in houses in cities or sub-urban areas.

3.2 The job search variables

Definition. The FLFS includes twenty-one questions about whether individuals took actions for searching for a job in a given reference week. We measure search intensity as the number of times an individual answered "yes" to some of these questions. More specifically, we select 11 questions and group them in order to represent three different search channels and compute the search intensity for each channel.[7] Figure 1 below details the list of questions within each of the job search channels we define.

[6] We could have used the FLFS as a panel of individuals and identified social interaction effects based on their variability across the quarters when each individual is observed as unemployed. However, only 57% of the unemployed individuals in the sample face two or more unemployment spells, which leaves us with not enough variability to identify these effects. Even if there were enough individuals observed unemployed several times, one could be skeptical about the variability of their neighbors characteristics within a six-quarters time period.

[7] We remove FLFS questions related to actions leading to entrepreneurship and passive search for a job, the answers to which are negative most of the time. We also remove other FLFS questions that tend to be consequences of previous job search actions (e.g. having an interview for a job, having done some missions with a temporary employment agency), or to which most of unemployed individuals answered no (e.g. participation to a professional fair or job forum.)

Table 1: Variables definition

Variables	**Definition**
Individual characteristics	
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.
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* include ex low-level white collars and blue-collar workers - *High-level occupations* include senior executives and higher intellectual occupations - *Unemployed (have never worked)* include unemployed who have never worked - *Other occupation* includes intermediate occupations, independent workers and farmers. It is the reference in the regressions, together with 0.8% of observations with missing values.
Foreigner	Having a non-French nationality.
Sex (female)	Male (the reference) or female.
Child	Having one child or more.
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 or not 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	Quarter time dummies over the period of analysis: Q12014 to Q42019, with Q12016 the reference.

Table 2: Variables definition

Variables	**Definition**
Explained variables	
Networks	Number of times an individual answered "yes" to the 3 FLFS questions regarding the use of personal and professional connections, including social media to find a job. See Figure 1 below for the list of questions.
Active	Number of times an individual answered "yes" to the 6 FLFS questions regarding active and direct actions leading to re-employment. E.g. entry tests, responding to job advertisements, direct approaches with unsolicited application.
Organizations	Number of times an individual answered "yes" to the 2 FLFS questions regarding contact with employment organizations. E.g. the French National Employment Agency, temporary employment agencies.
Total	Sum of the three previously defined variables.
Variables of interest: Endogenous effects	
Unemployed neighbors' av. search intensity	Average search intensity of unemployed neighbors in the cluster, individual i and her household members excluded, for each of the three job search channels (active, networks, organizations) or total search.
Unemployed neighbors' top search intensity	Maximum job search intensity of unemployed neighbors in the cluster, individual i and her household members excluded, for each of the three job search channels (active, networks, organizations) or total search.
Variables of interest: 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.
% low-level diploma	Share of unemployed neighbors in the cluster with a level of diploma inferior to the French baccalaureate, individual i and her household members excluded.
Variables of interest: 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.
% high-level diploma	Share of non-unemployed neighbors with an educational level superior to the French baccalaureate (graduate and post-graduate degrees), individual i's household members excluded.
% low-level diploma	Share of non-unemployed neighbors with an educational level inferior to the French baccalaureate (vocational diploma, middle school certificate, primary school certificate and no diploma), individual i's household members excluded.

Table 3: Descriptive statistics

	% of estimation sample
Age	
Age 15-29	39.0
Age 30-39	21.9
Age 40-49	19.1
Age 50-59	16.5
Age above 60	3.6
Female	49.2
Has one child or more	38.6
Nationality	
French	87.9
Foreigner	12.1
Education[a]	
High-level diploma	25.1
Baccalaureate	22.5
Low-level diploma	52.0
Missing	0.4
Previous occupation[a]	
Farmer	0.1
Independent worker	2.7
High-level occupation	6.9
Intermediate occupation	14.2
Low-level occupation	57.7
Unemployed (has never worked)	17.6
Missing	0.8
Partner's employment status	
Employed partner	30.1
Unemployed partner	3.6
Inactive partner	10.7
No partner	55.4
Missing	0.2
Dwelling's architectural environment[b]	
Scattered houses outside of urb. agglomerations	9.4
Houses in an urban or sub-urban environment	36.7
Flats in high-rise housing projects	20.3
Other flats in urban areas	28.0
Mixed housing	5.6
Type of area[c]	
Rural municipalities[c]	14.3
Urb. unit $<$ 10,000 inhabitants	7.7
Urb. unit 10,000 to 50,000 inhab.	10.3
Urb. unit 50,000 to 100,000 inhab.	8.9
Urb. unit 100,000 to 200,000 inhab.	7.7
Urb. unit $>$ 200,000 inhab. (except Paris)	33.8
Paris urban unit	17.3
N individuals	26,427

[a] See Table 1 for the definition of education and occupation variables.

[b] The architectural environment is defined in the FLFS data.

[c] Rural municipalities in the sample are municipalities below 2000 inhabitants part of an urban area. See note 5 for the definition of urban areas.

Figure 1: FLFS questions used to measure job search behaviors

Search through organizations
Q1: Have you contacted the French National Employment Agency (*Pôle Emploi* - personal initiative for job search or training), the Agency for the employment of Managers in France (*Association Pour l'Emploi des Cadres, APEC*), the chamber of commerce and industry or any other public institute?
Q2: Have you contacted one (or more) temporary employment (interim) agencies or a placement operator?
Active and direct search
Q1: Did you take part in an entry test for civil service?
Q2: Have you made a direct approach to an employer by personally submitting an unsolicited (speculative) application at a trade fair/a job forum or in the company?
Q3: Have you made a direct approach to an employer by sending an unsolicited application by post or e-mail or on the company's website?
Q4: Have you reviewed some job advertisements?
Q5: Have you responded to a job advertisement/offer?
Q6: Have you had a job search advertisement placed or posted, for example in a newspaper or on the internet?
Search through personal and professional networks
Q1: Have you turned to personal contacts such as family or friends to find a job or set up a business?
Q2: Have you turned to professional contacts to find a job or set up a business?
Q3: Have you shared via digital social networks that you are looking for a job, and made your professional profile known?
Total search intensity

Source: INSEE

The first job search channel refers to search through *contact with employment organizations* such as the French National Employment Agency (*Pôle Emploi*), the French Agency for the Employment of Managers (*APEC*), a placement operator, a temporary employment agency, the Chamber of commerce and industry, or any other public institute.[8] The second search channel refers to *active and direct actions leading to re-employment*. They include: entry tests, direct approaches with unsolicited applications, reviewing and responding to job offers, placing job search advertisements. The *job search through personal and professional networks* channel refers to the use of personal and professional connections to find a job, and includes the use of social media.[9] For the sake of readability, we will use the term "job search through networks" to refer to this job search channel. It is important to note that the term *networks* refers here to personal and professional acquaintances. This is not to be confused with the literature relating to the analysis of interactions on a network. Finally, the *total job search intensity* variable sums together the three previously defined variables and is a measure of search intensity in general.[10]

The literature usually defines job search behaviors as: (i) job search intensity (number of actions, time dedicated) and (ii) job search means or channels (which specific actions towards job search). Our job search measures cover both dimensions. For each of the actions mentioned, we do not know however how many actions were taken, nor the time spent. For instance, we cannot know

[8]In terms of contact with the French National Employment Agency, only the personal steps taken in the context of job search or training are included in this variable. Contacts related to mandatory follow-up interviews or contacts to solve a problem concerning the payment of unemployment benefits are not considered.

[9]Although our analysis is interested in highlighting the existence of neighborhood effects in the job search behaviors of the unemployed, the job search through networks variable is not limited to contacts with neighbors. We hypothesize that unemployed individuals imitate the job search behaviors of their neighbors but this does not mean that they only use networks within the neighborhood, they can also use family, friends and professional connections outside the neighborhood.

[10]Individuals may develop their search effort combining or not different channels, which could then appear as substitutable or rather complementary. We tested for such effects by regressing on the estimation sample each job search channel on the other two channels controlling for individual fixed-effects. All else being equal, the results show that job search channels are more complementary than substitutable, the highest complementarity being observed for active and direct search and search through networks.

how many times individuals have contacted friends, family members or professional connections to find a job. We only know whether or not they have used one of these three types of networks to find a job.

Distribution of job search variables. Table 4 describes the distribution of the four job search variables in the estimation sample. Given the number of related questions, the search through networks variable can vary up to a maximum of 3, the search through active and direct actions up to maximum of 6, the search through official employment organizations up to a maximum of 2 and the total job search intensity up to a maximum of 11.

The total search intensity variable is rather well distributed: 8.6% of individuals have a total search intensity of 1, 33.5% have a total search intensity that is either 2 or 3, 35.4% take 4 or 5 types of actions towards job search, while 22.6% have a total search intensity that is equal or superior to 6. Approximately one fourth of unemployed individuals in the sample do not search through networks, 60% have a search through networks intensity that is 1 or 2 while very few individuals have a search through networks intensity above 2. A majority (85%) of individuals carry between 1 and 3 types of direct and active actions towards employment, 6.9% do not use this type of job search channel, while very few carry more than 3 types of direct and active actions. Finally, 41% of the sampled individuals do not use job search through employment organizations, while another 59% contact 1 or 2 types of organizations.[11]

Table 4: Distribution (in %) of the job search variables in the estimation sample

Search intensity	0	1	2	3	4	5	6	7	8	9	10
Total	0	8.6	14.8	18.7	19.2	16.2	11.6	6.9	3.1	0.9	0.1
Networks	26.7	32.5	26.9	13.9							
Active	6.9	28.5	29.3	27.8	7.2	0.3					
Organizations	41.1	43.3	15.6								
Observations					56,602						

Source: French Labor Force Survey, estimation sample as defined in the text.
Reading notes: 19.2 % of unemployed individuals in the sample have a total search intensity of 4. The 56,602 observations correspond to 26,427 individuals interviewed when unemployed in different FLFS waves.

Individual determinants of job search channels. We anticipate a bit on the main estimated model, which will be presented in detail in section 4, and comment here on the estimated coefficients for the control variables to show how the job search measures are indeed influenced by individual characteristics (see table E.1 page 44 in the appendix for the estimated coefficients). Job search through networks is used more by the unemployed who were previously in high-level occupations or who have a graduate or postgraduate degree. It is also used more by unemployed people aged 30 to 49, the age group that is usually well integrated into the labour market. Women tend to search less through networks than men. Interestingly, having children encourages this type of job search, which could be interpreted as parenthood opening the door to wider networks. Having a partner who is employed also encourages job search through networks. Regarding the active type of search, being more educated, having a high position in the labor market or being young increases this type of job search, while having a child or being a foreigner

[11] A potential measurement error of the job search intensities could come from the order of appearance of the questions in the survey. Individuals interviewed could get fed up with the questionnaire and answer "no" to all the last job search related questions. We checked for that possible threat and find that the probability of answering "no" to a job search question is not related to its order of appearance in the survey. Moreover, the order of the questions used to compute the intensities is well distributed across the job search channels we defined. Also, interviews on our period of analysis are either conducted face-to-face or by phone which prevents surveyed individuals to answer no out of weariness.

decreases it. Search intensity related to active contact with official employment organizations is mainly used by individuals with less favorable characteristics regarding integration on the labor market. Being of a former low-level occupation, holding a low-level diploma or being foreigner indeed fosters search intensity through this channel. More generally speaking, unemployed individuals who have never worked before, or who have an inactive partner feature lower search intensities in each job search channel. The results regarding the impact of education seem to contradict previous observations by Ioannides and Loury (2004) and Vázquez-Grenno (2018). But overall, these observations regarding the individual job search determinants seem to go in the same direction as Bachmann and Baumgarten (2013) and Piercy and Lee (2019) and support the validity of the job search measures we use. The estimated coefficients for quarter time dummies (available upon request) are also as expected: individuals tend to search less during the third quarter, which includes the summer holidays (July and August) in France.

Mean job search intensities and local neighborhood characteristics. Given the previously described individual behaviors, job search behaviors averaged at the local neighborhood level are likely to be correlated to neighborhood social composition. The plots in Figure 2 aim at investigating for these correlations. They are based on a sample consisting of the 7,741 clusters used in the analysis, for a randomly drawn quarter for each of them. For each cluster, we compute the mean job search intensity for each channel and plot its relationship to the shares of employed in the whole population, of employed in high-level occupations among the employed population, and of unemployed in the whole population.
Consistent with the impact of individual characteristics, mean network search intensity in the local neighborhood significantly increases with the share of employed and high-level occupations in the neighborhood, and decreases with the share of unemployed. Mean active search intensity follows a similar pattern, but to a lesser extent in terms of magnitude, and with non-significant coefficients. This configuration changes for search through organizations, with mean intensity which significantly decreases with the share of high-level occupations in the neighborhood, and increases with the share of unemployed, the slope being however not significant. Overall, these plots outline the existence of local social composition effects in aggregated job search behaviors. Both network search and active search seem to be stronger in neighborhoods with high social composition levels, while the reverse seems to hold for search through organizations. These plots are only here for the sake of descriptive statistics as they do not control for spatial sorting across neighborhoods.

4 Empirical strategy

We reframe our research question within the larger stream of research on social interactions effects. Our aim is to identify the impact on unemployed individuals' job search behaviors of (i) unemployed neighbors' job search behaviors, that is endogenous effects in Manski's terminology, (ii) unemployed neighbors' characteristics, that is contextual effects, and (iii) other (employed or inactive) neighbors' characteristics. The influence of employed or inactive neighbors characteristics is not an interaction effects in the spirit of Manski's model in the sense that it is caused by a set of individuals that is distinct from the individuals for whom we analyze the job search behaviors and is therefore not subject to the reflection issue that we will discuss in this section. We will call it a "group effect" in the following. As previously explained, the individuals who are considered as neighbors live in the same cluster as the individual, a geographical scale at which interactions between neighbors are likely to take place.[12]

[12]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 neighborhoods-related social interactions, which can in fact intersect with friendship relationships, as these can be created within the

Figure 2: Correlations between cluster average job search measures and local characteristics

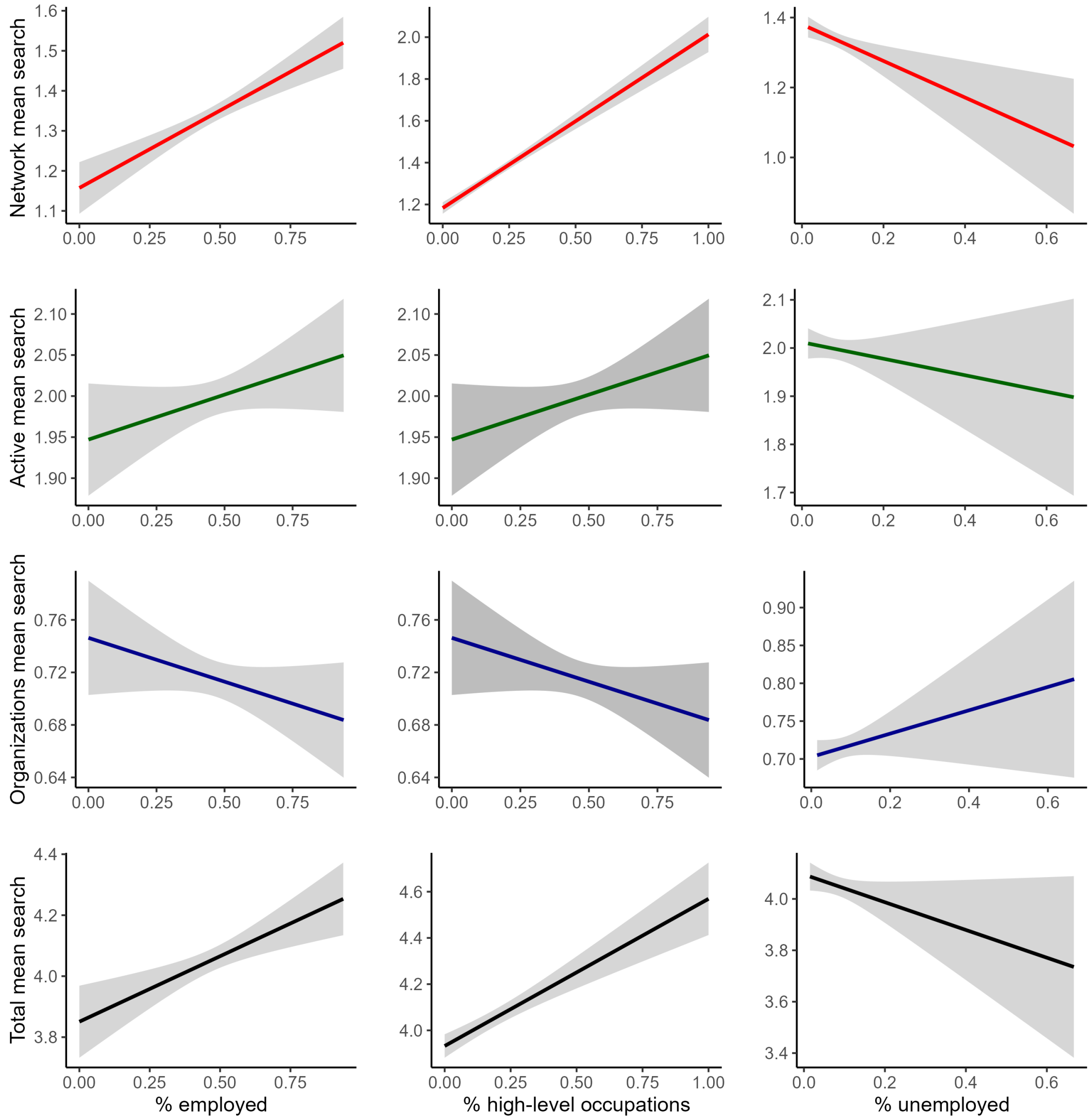

Figure 2 displays plots performed on a sample comprising the 7,741 clusters of the estimation sample. For each channel, mean job search intensity in the cluster is regressed on the cluster shares of employed (% employed), of employed in high-level occupations (% high-level occupations) and of unemployed (% unemployed).

Different mechanisms can explain the existence of *endogenous peer effects* in unemployed individuals' job search behaviors. First, psychological factors and social pressure, with the need to conform to the social norms promoted within the reference group, can be a cause to the occurrence of these imitative behaviors. If an unemployed individual lives in a neighborhood where being unemployed is frowned upon, and where her unemployed neighbors are actively looking for work, she might face a cost of deviating from the group's social norm and feel social pressure to act similarly. Second, the conformity 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 or higher utility levels. This seems all the more

neighborhood.

true as Caliendo et al. (2015) show that beliefs about the efficiency of the job search method and about the impact of one's own actions plays an important role in the search intensity. Nicodemo and García (2015) show in the case of Colombia that the use of networks vs. non-networks job search methods is influenced by neighbors' choices and the way they find employment. A higher proportion of neighbors using social networks for finding a job increases the probability to use the same channel.

We also consider the influence of neighbors' characteristics on job search behaviors. We first hypothesize that a low share of employed neighbors may push to a lower job search intensity as unemployed individuals may then have negative expectations about their chances of finding a job and less pressure to do so (Patacchini and Zenou, 2006). Beyond the psychological costs already associated to unemployment (implosion of the daily time structure, lower social status, stress and anxiety), such a context may push unemployed individuals to think that that they do not statistically stand out from the crowd, and can indeed lead to a discouragement in the job search effort. We also assume that a higher rate of employed individuals in a neighborhood raises the social stigma associated to unemployment. It might also offer better access to information on job opportunities and to a network that facilitates job search (Bayer et al., 2008; Topa and Zenou, 2015; Hellerstein et al., 2011, 2014). This is especially true if these employed individuals are in high-level occupations as they occupy positions that facilitate worker-firm matches through a better quality of information and the possibility of direct referrals to employers (Schmutte, 2015). We can easily imagine an encounter in the neighborhood between an employed and an unemployed neighbor. A few words would be enough to make the unemployed person's situation known or maybe the employed neighbor has heard about it by word of mouth. The latter could then share the job offers she knows about or offer other solutions, such as contacting her acquaintances to find a job. Another stem of the neighborhood effects literature shows that the higher the level of education in a neighborhood, the more individuals are immersed in a cultural environment that is more conducive to job search (Akerlof, 1980; Wilson, 1987; Crane, 1991; Cutler and Glaeser, 1997). Indeed, if unemployed individuals meet in their neighborhood highly-educated individuals, whom they may consider as role models, this will raise their will to find a job. 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*.

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, who have a university degree, and who have a low-level diploma, and the shares of employed neighbors who are in high-level occupations, and who are in low-level occupations, as defined in Table 1. These variables reflect the probability of running into someone in the neighborhood who is employed and therefore connected to the job market, or someone with a university degree who can provide some keys to finding a job. The share of low- and high-level occupation neighbors is computed among employed individuals. We want this last variable to reflect the probability to be in touch with individuals who are connected to the labor market, and in positions that may or not provide access to higher-quality information and who could potentially influence a future labor market match.

The variables for contextual effects are based on unemployed neighbors, for which only the diploma and the level of previous occupation are relevant. Moreover, due to the nearly zero distribution in the estimation sample of high-level categories (see Figure B.1, page 40 in the Appendix), we include only the effects of low-level characteristics (ex-low-level occupation, low-level diploma) of unemployed neighbors. Thus, the contextual effects we consider are a subset of the individual characteristics included in the model. This is justified by the hypothesized economic mechanisms listed above.[13]

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

4.1 The empirical model

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

$$Y_{igst} = \alpha + \beta \ \overline{Y}_{gst\backslash i} + \sum_{j=1}^{J} \gamma_j \ \overline{Z}_{jgst\backslash i} + \sum_{k=1}^{K} \delta_k \ \overline{W}_{kgst} + \sum_{l=1}^{L} \lambda_l X_{ligs} + \theta_t + \eta_{s_g} + \epsilon_{igst}$$

where

- Y_{igst} is search intensity of unemployed individual i in cluster g in sector s at quarter t; search through networks, through organizations, active and direct search, and total search intensities 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 collinearity;
- $\overline{Z}_{jgst\backslash i} = \frac{\sum_{u_i \in gst} Z_{j u_i}}{n_{u_i gst}}$ are J variables for contextual effects; in the main specification $J = 1$ and is the % of ex-low-level occupations among i's unemployed neighbors; 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 collinearity;
- $\overline{W}_{kgst} = \frac{\sum_{a_i \in gst} W_{k a_i}}{n_{a_i gst}}$ or $\frac{\sum_{e_i \in gst} W_{k e_i}}{n_{e_i gst}}$ are $K = 3$ variables for group effects: % of employed among i's non-unemployed neighbors, with $n_{a_i gst}$ their number, % of high-level, and % 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 so as to avoid a source of collinearity;
- 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 common to all individuals living in the same sector that impact search intensity; they help us to deal with location endogeneity.

Table 1 presents the definition of all explanatory variables in equation 4.1 and some variants used in the robustness checks. Figure B.1 in the Appendix gives an account 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.

[13]Note that we do not assume any impact of non-unemployed neighbors' job search behavior, since there is very little search by employed individuals.

4.2 Identification strategy

Two identification issues have to be thoroughly considered for the consistent estimation of neighborhood effects. The first identification problem to tackle is the location endogeneity issue, which corresponds to the *correlated effects* in Manski's terminology. There are two sources to these correlated effects. First, because of sorting on the housing market, individuals sharing the same observed and unobserved characteristics are likely to locate in the same neighborhoods. Moreover, this non-random sorting is reinforced by the existence of neighborhood effects, as individuals may choose a residential location based on anticipated local social interaction effects. Second, there are random shocks common to all individuals in a neighborhood. As a consequence, individuals living in the same neighborhood share similar unobservables, and not controlling for them would lead to biased estimations of neighborhood effects. To deal with this location endogeneity issue, we use a method first proposed by Bayer et al. (2008) and applied more recently by Grinblatt et al. (2008), Hawranek and Schanne (2014), Schmutte (2015), Solignac and Tô (2018) and with the use of the FLFS by Hémet and Malgouyres (2018, 2019) and Chareyron et al. (2021).

This strategy consists in using two nested levels of neighborhoods, the lowest one where the existence of social interactions is assumed, and the highest one, for which fixed effects are included in order to control for location choice at this level. We here include sector fixed effects, so that neighborhood effects are identified based on their variation at the cluster level within each sector. The identifying hypothesis is that even if households select a neighborhood where they want to locate, here a sector, they cannot select a specific location, here a cluster, within this neighborhood. This is credible because the FLFS offers a very narrow definition of neighborhoods, and sectors and clusters are only used as sampling units of the FLFS and do not correspond to any known frontier. If this assumption holds true, there is no correlation in the unobservables affecting an individual's job search behavior and the ones affecting her neighbors' behavior, so that any impact of her neighbors' behavior on the individual can be considered as causal. We provide in the robustness checks in Section 6 a statistical test aimed at supporting this identifying hypothesis.

A more subtle identification issue occurs in linear-in-means social interaction models where social groups are a partition of the population, individuals being affected by all individuals belonging to their group and by nobody outside the group. This induces a perfect collinearity between the mean outcome of the group, that is the endogenous effect, and the mean characteristics, that is the contextual effects. This issue is referenced to as a reflection issue following Manski's terminology. We deal with the reflection issue by following Lee (2007) and the development provided in Boucher et al. (2014). This strategy can intuitively be understood as deriving from two observations. First, in Manski's model, because individuals interact in groups including themselves, all individuals in a group have the same neighbors, hence the collinearity between endogenous and contextual effects. Second, as introduced by Moffitt (2001), exclusive averaging, which means that individuals are discarded from the computation of their peers' means, might solve this issue because each individual in a group has then her own reference group. But as Lee (2007) has shown, this is actually only the case when groups have different sizes.[14] Moreover, as shown by Boucher et al. (2014), the identification is stronger if groups size distribution is dispersed and if groups are small. We argue that the estimation sample we use fits these conditions, with a large number of groups of small and varied sizes. Indeed, the estimation sample comprises 30,873 local neighborhoods. The number of unemployed individuals per cluster is on

[14] See Bramoullé et al. (2009) for a formal and clear presentation of these arguments. Another, related identification strategy is used in the case of networks effects, in which case reference groups only partially overlap, so that peers of peers are not peers. However, we do not have access in the FLFS to the geolocation of dwellings, that would allow to use individual-specific reference groups.

average 1.83, with a standard deviation of 1.18 and can go up to a maximum of 14 (see Table I.1 and Figure B.1 in 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 uses the fact that within each group, each individual has a specific group of peers thanks to exclusive averaging, so that the aggregate characteristics and contextual variables 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, here other unemployed individuals in the same cluster (Lee, 2007). This allows to estimate the model using a conditional quasi-maximum likelihood estimator developed for SAR models, as suggested by Lee (2004). This is the estimator we use here.[15]

Finally, note that we consider that the explained variable in our analysis is not a discrete choice variable but rather, as in Davezies, D'Haultfoeuille, and Fougère (2009), a continuous variable, that is how intensely an individual searches for a job through a given channel, observed as a discrete variable, namely how many times the individual answered yes to a set of questions on the job search in the FLFS.[16]

5 Results

Table 5 presents the estimated coefficients for the variables of interest of equation 4.1, while Table E.1 in the Appendix presents those of the control variables. Table 6 and Table E.2 in the Appendix display the magnitude of the effects for the variables of interest and the control variables respectively.

Endogenous effects. Table 5 points to the presence of positive and highly significant endogenous effects for total search intensity and for each of the three job search channels. This tends to show that the more unemployed neighbors search for work, the more individuals do so. Table 6 shows that the implied effects are stronger for search through networks than for the other channels: a one standard deviation increase in the endogenous effect increases (with regards to mean search intensity) this type of job search by 5.4% against 2.5% and 3.4% respectively for active and direct search, and search through organizations. Such results suggest that unemployed individuals might face social pressure to act similarly as others in the same situation as them and to conform to the behaviors and social norms promoted within the neighborhood, known as a place of socialisation. If an individual lives in a neighborhood with many unemployed people who search very little, she might be tempted to do the same. On the contrary, if she lives in a neighborhood where on average unemployed individuals are actively looking for a job, she should be encouraged by an imitation effect to do the same. These endogenous peer effects could also

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

[16] In doing so, we favor the use of the identification strategy developed by Lee (2007) over the use of nonlinearity as an identification strategy. An early attempt at developing count data models with peer effects is proposed by Houndetoungan (2024).

occur through the exchange of information between unemployed neighbors who, facing the same situation, would either help and advise each other regarding job search or discourage each other (*"You will not find a job. The economic situation is bad"*).[17]

Table 5: Main regression results

	Explained variable			
	Total	Networks	Active	Organizations
	(1)	(2)	(3)	(4)
Endogenous effects				
Un. neighbors' average intensity	0.049***	0.074***	0.051***	0.043***
	(0.004)	(0.004)	(0.004)	(0.004)
Group effects *(among non-unemp. neighb.)*				
% employed	0.107	0.091**	−0.017	0.023
	(0.069)	(0.036)	(0.040)	(0.027)
% low-level occupations	−0.217***	−0.121***	−0.101***	0.009
	(0.055)	(0.028)	(0.032)	(0.021)
% high-level occupations	0.028	0.078*	−0.039	−0.013
	(0.081)	(0.042)	(0.047)	(0.031)
Contextual effects *(among unemp. neighb.)*				
% ex-low-level occupations	−0.080***	−0.041***	−0.053***	−0.004
	(0.020)	(0.010)	(0.011)	(0.008)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Log-likelihood	-106,552	-71,093	-77,138	-55,388
N (Obs./ Sectors/ Clusters x t/ Indiv.)	56,602	/ 2,621	/ 30,873	/ 26,427

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

Note: See Table 2 for a detailed presentation of the independent variables.

Group effects. We find a positive effect of the share of employed individuals in the neighborhood for network search intensity (Table 5, column 2). We interpret this group effect firstly as capturing the perception of the unemployment status in the neighborhood. If an unemployed individual lives in a neighborhood where few unemployed and where the unemployment status is (unconciously) frowned upon, then she might face social pressure to find a job rapidly, which increases job search intensity. It secondly captures whether unemployed individuals are surrounded by neighbors connected to the labor market who would make it easier to obtain information on job opportunities, which is why it is not surprising that the results are significant only for job search through personal and professional network which increases by 1.2% (with regards to mean search intensity) for a one standard deviation increase in the share of employed in the neighborhood (Table 6, column 2).

Regarding the level of occupations of these employed neighbors, we find a positive effect of the share of neighbors in high-level occupations for search through networks (at the 10% risk level), and a negative effect of the share of low-level occupations neighbors for total search, search

[17] Given that the literature has shown that search intensity declines over the unemployment spell (Faberman and Kudlyak, 2019; Krueger and Mueller, 2011), one could be worried that similar unemployment duration for neighbors surveyed at the same point in time could drive a systematic correlation between the individual's and her neighbors' job search behaviors, that would explain the endogenous effect. We tested for that possible threat by estimating an alternative specification that includes the average unemployment duration of neighbors. Adding this variable does not change the results on endogenous effects, which are therefore not driven by this correlation. These results are available on request.

through networks and active and direct search. Again, the job search channel for which the occupation of neighbors seems to have more impact is search through networks. A one standard deviation increase in the share of high-level occupations increases (with regards to mean search intensity) search through networks by 1.1%, while a similar increase in the share of low-level occupations decreases search through networks by 2.4%, and both total search and active search by 1.3%. Occupation reflects position on the labor market. It captures the quality of the connection of neighbors to the labor market. One of the possible networks unemployed can call upon are those neighbors in high-level occupations who could easily recommend them to one of their acquaintances, or own information of quality on job opportunities. Being surrounded by neighbors in high-level occupations also implies being in an environment that may be conductive to job search, where individuals look harder because they feel that they have better chances of finding a job, where they can cross paths with one of these "role model" neighbors who can help in giving various keys related to job search or who can indirectly/inconciously induce more pressure on the unemployed to return to work. The reverse mechanisms apply to the group effect related to low-level occupation neighbors. The group effects for search through organizations are all non-significant. This is not surprising as it corresponds to the more "official" and traditional ways of finding a job and to the minimal actions to be taken when unemployed.

When we compare in Table 6 the magnitudes related to a one standard deviation increase in the endogenous and the group effects variables, we can see that they are always higher for the endogenous effects. Also, for group effects, large changes in the population composition would be required to impact individual job search behaviors, while the increase needed in the search intensity of unemployed neighbors to have an effect seems more plausible. For instance, an increase by 17.5 percentage points (1 s.d) in the share of neighbors in high-level occupations (which would be a huge increase given that the average is equal to 4.2%; see Table C.1) would be required to increase search through networks by 1.1%, while an increase by 0.92 (1 s.d) in the average network search intensity of neighbors, that is still doubling the mean value, would lead to a 5.4% increase in the individual job search intensity.

Table 6: Magnitudes of social interaction effects - main specification

	Impacts for 1 s.d. in the dependent variable			
	Total (1)	Networks (2)	Active (3)	Organizations (4)
Endogenous effects:				
Un. neighbors' average intensity	+2.7%	+5.4%	+2.5 %	+3.4%
Group effects: *non-unemployed neighbors*				
% employed	NS	+1.2%	NS	NS
% low-level occupations	−1.3%	−2.4%	−1.3%	NS
% high-level occupations	NS	+1.1%	NS	NS
Contextual effects: *unemployed neighbors*				
% ex-low-level occupations	−0.8%	−1.4%	−1.1%	NS
Mean of JS variables	4.03	1.28	2.01	0.75
s.d of JS variables	1.88	1.01	1.07	0.71

Table 6 presents the magnitudes of the effects derived from the estimated coefficients in Table 5. Reading direction: a 1 s.d increase in the average total search intensity of unemployed neighbors increases total search by 2.7% (with regards to mean intensity).

Contextual effects. We find a negative impact of the share of unemployed individuals in low-level occupations for total search, search through networks and active and direct search. This is in line with the group effect of low-level occupations neighbors. The magnitudes are close to the corresponding group effect's magnitudes (Table 6).[18]

Results with diploma. The main specification presented in equation 4.1 is supplemented by a second one in which the characteristics in terms of occupation are replaced by characteristics in terms of diploma. We do not include occupations and diploma in the same specification to avoid collinearity between these characteristics. $\overline{Z}_{jgst\backslash i} = \frac{\sum_{u_i \in gst} Z_{ju_i}}{n_{u_i gst}}$ is then the percentage of low-level diplomas among i's unemployed neighbors. $\overline{W}_{kgst} = \frac{\sum_{a_i \in gst} W_{ka_i}}{n_{a_i gst}}$ consists of the percentage of employed, university graduates, and low-level diplomas among i's non-unemployed neighbors. In X_{ligs}, previous occupation is replaced by diploma. The estimated results of this specification (see Table D.1 in the Appendix) confirm the findings regarding the endogenous effects. As for the group effects, most of them are non significant, which underlines that the position of neighbors on the labor market seem to prevail on neighbors' educational background in neighborhood effects on job search behaviors. The only exception is the positive effect of highly educated neighbors on search through networks which seems more important than that of high-level occupation neighbors (see Table D.2 for the magnitudes of effects).

Heterogenous effects: comparing dense to non dense sectors. A question that naturally arises from the previous results is whether these social interaction effects differ by type of built environment or depending on population density. Are they stronger or weaker in more densely populated places? In an attempt to answer this question, we provide an heterogeneity analysis in which we run our main model on two separate samples defined depending on density. We measure density on the basis of a FLFS variable that describes the architectural environment of a dwelling. A dwelling is considered to be in a dense area if its surroundings consist of flats in city blocks or in high-rise housing projects. We define a sector as “dense” if more than 75% of the dwellings in it are located in dense areas. Tables G.1 and G.2 in the Appendix outline the results for the two sub-samples, while Tables G.3 and G.4 in the Appendix describe the magnitudes of the effects.

A first important observation is that the magnitudes for the endogenous effects related to the three job search channels and total search are higher in dense sectors compared to non dense sectors. A one standard deviation increase in the endogenous effect increases (with regards to mean search intensity) total search by 3.7%, search through networks by 6.8%, active search by 3.8% and search through organizations by 3.9% in dense sectors, against 2.2%, 4.4%, 2.6% and 3.5% respectively in non dense sectors. We also find stronger contextual effects in dense areas than in non dense areas. A one standard deviation increase in the share of unemployed neighbors in low-level occupations decreases total search by 1.4%, search through networks by 1.9% and active search by 1.5% in dense sectors against 0.6%, 1.1% and 0.9% respectively in non dense sectors. The same holds for group effects with a higher magnitude of the effect related to the share of neighbors in low-level occupations in dense than in non dense sectors.[19] We also have two group effects in search through organizations that are present in dense sectors and not in non dense sectors: a simultaneous positive effect of the share of employed neighbors and negative effect of the share of these neighbors in high-level occupations. Altogether, these

[18] We tested the stability of the endogenous effect coefficient as a function of the inclusion of contextual and group effects with a horse race exercise in which the contextual and group effects are gradually added to the endogenous effect. For the sake of brevity, only the results for the network search channel are presented in tables F.1 and F.2 in the appendix. We observe a stability of the endogenous network coefficient when contextual effects are added, which supports the robustness of our main results as well as the validity of the identification strategy that allows to estimate endogenous and contextual effects separately.

[19] A one standard deviation increase in this share decreases total search by 1.6% and search through networks by 2.9% in dense sectors against 1.1% and 4.4% respectively for non dense sectors. The negative coefficient of the share of neighbors in low-level occupations for active search is not significant in dense sectors.

results seem to underline that social interaction effects are stronger in denser environments. This suggests that, contrary to the common view that denser urban environments are synonymous with anonymity, social ties are active in these neighborhoods and influence individual job search behavior. This observation about dense neighborhoods was also made by sociologists in the study *"Mon quartier, mes voisins"*.

As a conclusion for this section, we note that the results for the endogenous, contextual and group effects highlight the existence of social interaction effects in job search behaviors, with imitation and spread of information effects mainly for job search through networks. The endogenous effects suggest the existence of a social multiplier effect. The group and contextual effects emphasize the importance of being surrounded by neighbors with strong labor market connections, which is likely to translate into unemployment inequalities across neighborhoods. These findings are consistent with what was observed by sociologists in the aforementioned survey *"Mon quartier, mes voisins"*, namely that neighborhood relationships remain at high levels in France and can play a role in job search via exchanges of information on job opportunities.

6 Robustness checks

6.1 Alternative measurement of search intensities

As explained in subsection 3.2, the dependent variables in the main part of the analysis are counts of the different types of actions taken by the unemployed person to look for a job. This is the simplest way to synthesize the 11 main FLFS questions on job search. Compared to other measures used in the job search literature, these measures have some limitations. First, they do not necessarily reflect the amount of time individuals spend looking for a job. Second, they do not take into account the efficiency of different types of job search activities. Although the data do not allow us to observe the time spent on these actions, we want to propose here a different way to synthesize the 11 job search variables of the FLFS taking search efficiency into account.

To do this, we draw on a literature that has used item-anchored scales that weight variables according to how well they predict a later outcome (Bond and Lang, 2018; Nielsen, 2019; Aliprantis and Tauber, 2024). In our case, this amounts to weighting the 11 FLFS questions according to how well they predict finding a job. In this way, we may have measures of job search that are more appropriate for revealing peer effects. Indeed, it may be the case that peer influence is stronger the more efficient the corresponding job search activities are. For example, if contacting a former colleague or boss is an efficient way to find a job, it should lead to more imitation behavior. Thus, if we give more weight to this type of action in the job search measure, we might find stronger peer effects.

Specifically, we construct a dataset that includes all observation periods of the individuals in the peer effect estimation sample, and we define a dummy variable that takes the value 1 if the individual is unemployed in the previous quarter and employed in the current quarter. We then regress this dummy variable on the 11 questions about job search activities in the previous quarter using OLS.[20] We do this using the individual panel dimension of the data, in order to control for individual unobservables. The estimated coefficients are then used as weights to compute weighted sums of the job search item answers, which provides a new total job search measure. We repeat the same procedure for the three distinct channels using the corresponding

[20] Since we are only interested in obtaining weights to construct synthetic indexes of job search activities and not in performing causal analysis, we keep things simple and do not model unemployment duration.

items.

Another advantage of these alternative measures of search intensities is that the four variables are now part of a more comparable scale, as they are likely to vary between 0 and 1.[21] Correlation coefficients between the initial job search variable, and the synthetic job search variable is 0.83 for total search, 0.99 for job search through networks, 0.84 for active and direct search, and 0.95 for search through organizations.

Table 7: Results with synthetic job search indexes

	Explained variable			
	Total	Networks	Active	Organizations
	(1)	(2)	(3)	(4)
Endogenous effects				
Un. neighbors' average intensity	0.027***	0.072***	0.032***	0.031***
	(0.004)	(0.004)	(0.004)	(0.004)
Group effects *(among non-unemp. neighb.)*				
% employed	0.004	0.008**	−0.001	0.005
	(0.003)	(0.003)	(0.003)	(0.003)
% low-level occupations	−0.007***	−0.011***	−0.006***	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
% high-level occupations	−0.001	0.007*	−0.001	−0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Contextual effects *(among unemp. neighb.)*				
% ex-low-level occupations	−0.002*	−0.004***	−0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Log-likelihood	57,633	57,957	58,202	55,727
N (Obs./ Sectors/ Clusters x t/ Indiv.)	56,602 /	2,621 /	30,873 /	26,427

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

Note: See Table 2 for a detailed presentation of the independent variables.

Table 7 above outlines the estimated coefficients for the synthetic job search variables, and Table 8 the corresponding effects magnitudes. We find here positive and highly significant endogenous effects for each of the job search channels and for total search intensity. The endogenous coefficient is, as before, higher for search through networks. The findings regarding group and contextual effects also seem to go in the same direction as in the main results. Job search, and more particularly, job search through networks, is affected by the position of employed neighbors on the labor market, and by the former occupation of unemployed neighbors.

Comparing the peer effects magnitudes for these new measures of job search (Table 6) to those related to general job search behaviors shows a slight decrease. A one standard deviation increase in the endogenous effect increases (with regards to mean search intensity) total search by 2.7%, search through networks by 5.4%, active search by 2.5% and search through organizations by 3.4% against 2.7%, 5.4%, 2.5% and 3.4% respectively before. The reduction in magnitude seems to particularly hold for total search, active and direct search and search through organizations, for which we also find lower levels in the group and contextual effects. For the new measure of

[21] As we estimate a linear probability model, they might take values outside of this range but this is here not the case. The new total search variable varies between 0 and 0.4, with a mean of 0.23. The new search though networks variable varies between 0 and 0.27, with a mean of 0.12. The new active and direct search variable varies between 0 and 0.33, with a mean of 0.22. The new search through organizations variable varies between 0 and 0.24, with a mean of 0.09.

Table 8: Magnitudes of social interaction effects - synthetic index

	Impacts for 1 s.d. in the dependent variable			
	Total (1)	Networks (2)	Active (3)	Organizations (4)
Endogenous effects:				
Un. neighbors' average intensity	+1.4%	+5.1%	+1.6 %	+2.5%
Group effects: *non-unemployed neighbors*				
% employed	NS	+1.1%	NS	NS
% low-level occupations	−0.7%	−2.3%	−0.7%	NS
% high-level occupations	NS	+1.0%	NS	NS
Contextual effects: *unemployed neighbors*				
% ex-low-level occupations	−0.4%	−1.0%	−0.6%	NS
Mean of synthetic JS variables	0.233	0.121	0.223	0.093
s.d of synthetic JS variables	0.087	0.092	0.086	0.091

Table 8 presents the magnitudes of the effects of the estimated coefficients in Table 7. Reading direction: a 1 s.d increase in the average synthetic total search intensity of unemployed neighbors increases total search by 1.4% (with regards to mean intensity).

search through networks intensity, the magnitudes related to endogenous, group and contextual effects variables are very similar to those in the main results.

Even if the magnitudes tend to reduce a bit for total search and two of the three job search channels, the novelty with these results is that we are able to underline the presence of peer effects in the job search behaviors that are more favorable to employment. We do not find evidence of stronger peer effects for these measures, which tends to show that peer effects do not favor the most efficient job search means. Other considerations (visibility, cost reduction) might have more influence.[22] More important, similar peer effects (both in terms of significance and magnitudes) are found for general search through networks behaviors and search through networks behaviors more favorable to employment.

6.2 Location endogeneity issue

Test for the absence of sorting across clusters within sectors. The strategy we use to control for location endogeneity is based on the hypothesis that there is no sorting within sectors, that is, the location of individuals within sectors is random, so that once we control for sector fixed effects, there is no correlation between an individual's and her neighbors' unobservables. An indirect test of this hypothesis, suggested by Bayer et al. (2008) and used by Hémet and Malgouyres (2018) on the FLFS, consists in estimating the correlation between neighbors' and individual's observed characteristics when controlling for sector fixed effects. If this correlation is null, this suggests that the same holds for unobservables.

We conduct this test by first regressing both an individual's characteristic and the exclusive average of the same characteristic among neighbors in the cluster on sector fixed effects.[23] The residuals from these two regressions, which measure the deviations from the sector average, are

[22]It might be interesting to investigate each of the different types of action to find the ones the most influenced by neighborhood effects. However, at this stage, we cannot estimate the SAR model with binary variables, and the formal development of suitable econometric methods for identifying peer effects in binary variables is still ongoing.

[23]As for endogenous and contextual effects, the individual herself and her household's members are removed in the calculation of the neighbors' average.

then regressed on each other. The R-squared of this regression measures the intensity of the correlation between these deviations from the sector average, and thus the intensity of sorting on the selected observable between clusters within sectors. As explained in Bayer et al. (2008), the use of exclusive averaging could lead to mean reversion, as high-level individuals are associated with low-level neighbors, and vice versa. This could lead to a systematic negative correlation between the individual and the average of her neighbors, which is avoided by taking only one randomly selected individual per cluster. For each of the selected observed characteristics, the procedure is repeated 200 times each time on a different random sample.

The mean R-squares computed over these 200 repetitions are reported in Column 3 of Table 9 for dummy variables describing education, previous occupation and citizenship, and mean age, and for three different sets of neighbors, the first two being non-unemployed neighbors and employed neighbors (Panels A and B), who are taken into account in group effects, and the third being unemployed neighbors (Panel C), who are taken into account in contextual and endogenous effects. For comparison, column 1 reports the R-squares without fixed effects (more precisely, the R-squares of the regression of individual characteristics on the neighborhood average), and column 2 reports the R-squares of the procedure with fixed effects at the urban unit level.[24] The values in column 1 are expected to be high due to spatial sorting at the neighborhood level. Since sorting between clusters within urban units is still important, the R-squares in column 2 should still be significant, while the R-squares in column 3 are expected to be low.

Overall, the R2 values decrease when going from the regression with no conditioning (Column 1) to the regression conditioning for sector (Column 3). This is clear for all non-unemployed neighbors and employed neighbors. For example, the diploma (low and high), which is subject to some correlation when not controlling for any FE, does not show any significant correlation when conditioning on the sector level. The within-sector average correlation of low diploma between the individual and her neighbors is 0.158 (Column 3). The R-square for being of foreign citizenship decreases from 7.358 with no fixed effects to 0.051 with sector fixed effects. All of the correlations when controlling for sector average composition are below 1.

As for the correlations between individual characteristics and that of her unemployed neighbors, one first notes that the values with no fixed effects are lower for the two other sets of neighbors. When conditioning on the sector level, all correlation values are low. In particular, when one looks at the characteristics exhibiting the highest level of segregation in general (namely education and nationality), the values of R2 when controlling for sector are below 1. Things are a little less clear for occupations. In this case, the correlation values are higher when conditioning on the sector level than without conditioning. However, these values remain low, with the highest value being 1.7% for executives, a category which is not very frequent on this sample of unemployed individuals.

One should also note that this test can be conducted on the different sets of neighbors only for individuals with at least one neighbor part of these respective sets. While the whole sample comprises 7,741 clusters, the subsample for the non-unemployed neighbors test has the same number of clusters (all unemployed individuals in the sample have at least one non-unemployed neighbor), the subsample for employed neighbors contains 7,712 clusters, and the subsample for unemployed neighbors, which by definition excludes isolated unemployed, has only 5,301 clusters. It could be the case that these clusters are more segregated than others, which would explain the slight correlation observed here.

[24] We also computed the R-squares with municipality fixed effects, but we do not show the results here because there is actually not much difference in the sample between municipalities and sectors, since only large municipalities in the sample have multiple sectors.

Table 9: Correlation between individual and neighbors' average characteristics

	Fixed effects		
	None	Urban unit	Sector
Panel A: All neighbors			
Education			
High-level diploma	8.287	5.365	0.091
Baccalaureate	0.216	0.127	0.005
Low-level diploma	7.864	5.056	0.165
Previous occupation			
Indep. worker	0.056	0.020	0.005
Executive	6.256	3.992	0.167
Intermediate prof.	0.577	0.367	0.004
Blue-/white-collar workers	2.072	1.624	0.117
Citizenship			
French	7.200	3.781	0.052
Foreign	7.274	3.811	0.053
Mean age	0.659	0.528	0.075
Observations (cluster × quarter)		30,873	
Panel B: Employed neighbors			
Education			
High-level diploma	7.135	4.684	0.131
Baccalaureate	0.034	0.012	0.021
Low-level diploma	6.053	3.898	0.121
Previous occupation			
Indep. worker	0.078	0.027	0.002
Executive	6.338	4.236	0.221
Intermediate prof.	0.354	0.239	0.001
Blue-/white-collar workers	3.830	2.595	0.240
Citizenship			
French	5.884	3.001	0.067
Foreign	5.892	3.007	0.067
Mean age	0.681	0.443	0.059
Observations (cluster × quarter)		30,716	
Panel C: Unemployed neighbors			
Education			
High-level diploma	2.197	1.075	0.793
Baccalaureate	0.044	0.002	0.992
Low-level diploma	2.300	0.999	0.677
Previous occupation			
Indep. worker	0.015	0.030	1.269
Executive	1.139	0.389	1.709
Intermediate prof.	0.159	0.026	1.081
Blue-/white-collar workers	0.696	0.205	0.836
Has never worked	0.196	0.052	0.443
Citizenship			
French	3.099	1.167	0.503
Foreign	3.113	1.171	0.507
Mean age	0.425	0.119	0.601
Observations (cluster × quarter)		15,647	

Note: Each cell in this table reports a R-square estimated as follows: on a randomly drawn sample with one observation by cluster, we regress both an individual's characteristic and the exclusive average of the same characteristic among neighbors in the cluster on fixed effects. The residuals of these two regressions are then regressed on each other. The procedure is repeated on 200 different 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. The R-squares are expressed in percentages, so that 8.296 means that the RHS variable explains 8.296 percent of the LHS variable's variance. Panel A corresponds to results of the test in which the cluster average is computed on non-unemployed neighbors aged above 15. In panel B the cluster average is computed on employed neighbors aged above 15, and in panel C the cluster average is computed on unemployed neighbors.

Taken together, we believe that these tests provide evidence that the identifying assumption we use to deal with location endogeneity is valid.

Controlling for potential group endogeneity. The main results presented thus far are valid under the assumption that the cluster in which the individual resides is randomly selected, conditional on the sector choice. We have provided above a test that supports this hypothesis, based on individual observed characteristics, and which has been utilized in the existing literature in similar contexts.

This test has however two limitations. First, by definition, it does not include isolated individuals, who are nevertheless present in the estimation sample. One could think that unemployed individuals who are alone in a cluster may be in a more privileged social environment and may also behave differently as regards job search. Second, this test relies on observables rather than unobservables. An argument in favor of using observables is that they are likely to induce a stronger correlation than unobservables simply because they are observable (Altonji et al., 2005). Still, one could ask whether the location exogeneity hypothesis is formally satisfied. The answer requires a test that takes unobservables into account.

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). Below, we provide a robustness check based on estimating a dyadic network formation model following Graham (2017) and Houndetoungan (2024).

In our case, 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:

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

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. This probability is estimated using observed covariates related to social distance for each pair of individuals. These covariates include a set of dummies for both individuals having a child, both being former high-level workers, both having never worked, both being foreigners, and the difference in their unemployment duration in months. Given the symmetry of the links, a single fixed effect is estimated for each individual. The individual heterogeneity fixed effects account for all unobservables that affect location choice in a cluster within a specific sector.

In a second stage, following Johnsson and Moon (2021), the peer effect model is estimated including a smooth transformation (namely a piecewise cubic polynomial approximation) of the individual fixed effect derived from the network formation model.[25] This method is analog in spirit to using a control function and allows to control for the correlation between the unobservables influencing location choice and the unobservables impacting job search behavior. These unobservables can be related for example to the attachment to the labor market or to the level of unobserved human capital.

[25] These estimations are performed using the Cdatanet R package written by A. Houndtoungan.

Table 10: Results with network formation model

	Total search intensity			
	Baseline sample		W/o isolated indiv.	
Network formation model	No	Yes	No	Yes
Endogenous effects				
Un. neighbors' average intensity	0.049^{***}	0.078^{***}	0.053^{***}	0.052^{***}
	(0.004)	(0.004)	(0.005)	(0.005)
Group effects *(among non-unemp. neighb.)*				
% employed	0.107	0.134^{*}	0.084	0.084
	(0.069)	(0.069)	(0.093)	(0.093)
% low-level occupations	-0.217^{***}	-0.208^{***}	-0.388^{***}	-0.396^{***}
	(0.055)	(0.055)	(0.071)	(0.071)
% high-level occupations	0.028	0.029	-0.116	-0.128
	(0.081)	(0.081)	(0.117)	(0.116)
Contextual effects *(among unemp. neighb.)*				
% ex-low-level occupations	-0.080^{***}	0.047^{*}	0.051^{*}	0.050^{*}
	(0.020)	(0.024)	(0.026)	(0.026)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Log-likelihood	-106,552	-106,475	-74,628	-74,615
N (Obs./ Sectors/ g x t/ Indiv.)	56,602 /2,621 /7,741 /26,427		40,343 /2,369 /5,019 /20,831	

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

Controls: individual's characteristics, quarter dummies and sector FE

Table 10 presents the results of this test. In Column 1, the baseline results are reported. In Column 2, results for the specification controlling for the individual heterogeneity effects derived from the network formation model are presented. Columns 3 and 4 show the results of these two specifications on a subsample excluding isolated individuals (see below).

One first notes that controlling for network endogeneity does not cancel out the endogenous effect. In fact, the estimated coefficient is increased. At the very least, this result suggests that the endogenous effect we find in the main results is not due to sorting into clusters within sectors. In line with the shift in the estimated coefficient for the endogenous effect, the model log-likelihood increases slightly when network endogeneity is taken into account. These results imply that the unobserved individual factors that influence cluster choice also impact total search intensity.

Given this role of individual heterogeneity effects, we take a closer look at their distribution. A bimodal distribution is observed, linked to the fact that isolated individuals have, all other things being equal, a low probability of forming ties. We also note that these individuals have a higher job-seeking intensity than those having unemployed neighbors. They generally seem to live in less dense, and possibly more privileged environments (see Table H.1 in the Appendix).

To gain further insight into this issue, we estimate the model on a subsample that excludes isolated individuals. The results of the main specification are presented in Column 3 of Table 10, and the results of the estimation including the control function based on the network formation model are presented in Column 4. We observe that the endogenous peer effect on this reduced sample is higher than on the whole sample, and also that controlling for group endogeneity on this subsample does not change the endogenous effect coefficient. This observation tends to support the idea that location endogeneity is adequately dealt with on the sample of non-isolated individuals with our identification design. In the R2 test above, we observed, on the same sample excluding isolated individuals, a slight increase in R2 when switching from no fixed effects to sector-fixed effects (Table 6.2, panel C). As the R2 remained very low, we concluded that our method for dealing with location endogeneity was valid. The present results confirm this previous conclusion.

We also find that the significance of the contextual peer effect reduces to the 10% risk level when controlling for network endogeneity, and that it becomes positive.

This new set of results suggests that location endogeneity is properly accounted for in our empirical design. First, it is adequately taken into account with our main design on the sample of non-isolated individuals, as shown by the lack of impact of controlling for group endogeneity on the estimate of the endogenous peer effect for this subsample and on the model log-likelihood (Columns 3 and 4). Second, the job search behavior of isolated individuals appears to be higher than that of others, which could be interpreted as the result of some social control, as unemployed individuals with no other unemployed in their cluster consider it more important to search more intensely. This specificity of isolated individuals can be dealt with in the specification that includes the network formation fixed effects.[26] In this case, the existence of the endogenous effect is confirmed and higher than in the main results.

In conclusion, we believe the results of this test confirm our main results. They stress the fact that only the presence of isolated individuals in the sample produces some group endogeneity not controlled for by our design. This test also points to potential negative biases in the endogenous and contextual effects estimates in our main results. In any case, and given the value of the endogenous effects on the subsample of non-isolated individuals, we believe that the value we found in our main specification is reliable.

Discarding public housing clusters. An important feature of the French housing market is the existence of a rather large share of public housing, which represented 15.6% of the housing stock in 2021.[27] Public housing units are rented by public housing offices at below-market rents and most of them are built as large multi-family buildings. They house mostly low-income households, are usually spatially concentrated, while the share of unemployed and low-skilled individuals in these dwellings is higher than in other parts of the housing stock.

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. In order to deal with this potential issue, we perform 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. We believe these additional results to be a relevant way to check that the main results are not driven by the comparison between households belonging to the two segments of the housing market. With this test, the estimation sample is reduced by 42%, the number of sectors by 333 and the number of local neighborhoods by 2,289, that is, 29% of those present in the main sample are discarded.

[26] Note that we keep the isolated individuals ni the sample for two reasons. First, this avoid creating a sample selection issue. Second, having these individuals in the sample improves the identification of the coefficients for individual characteristics.

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

Results in Panel A of Table 11 show a general stability with regards to the endogenous effects, which are for each of the job search variables very significant (despite an increase in standard errors due to the lower sample size) and steady in terms of coefficients, with again a higher value for search through networks than for the other channels. This is a key element as the results regarding these imitation and diffusion of information effects are the overriding findings in our main results. The contextual effects related to ex-low-level occupation neighbors are almost identical to those in the main results.

As far as group effects are concerned, it should be kept in mind that these variables have, by construction, the same value for all unemployed in a cluster. Thus, their identification relies on cluster-level variation within sectors. By removing clusters with public housing, we significantly reduce the number of clusters per sector, which then directly affects the identification of group effects. We also change the type of unemployed in the sample, mainly in terms of education, occupation and nationality (table H.2, column B). Nevertheless, the impact of the share of neighbors in low-level occupations, which is strong in the main sample, here also affects negatively total search, search through networks and active search, highlighting again the importance of the quality of neighbors' connection to the labor market. However, the previously significant impact of the share of high-skilled neighbors on network search disappears. The most important change is for the impact of the share of employed neighbors on search through networks, which changes both in terms of value and standard error, possibly for the reasons mentioned above.

In summary, these additional results do not call into question the main results. They head in the same direction and 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.

Removing heterogenous sectors. Another potential source of bias related to location endogeneity is the existence of clusters with striking quality differences within sectors, for example in cases in which moving from one street to the next implies environments that differ a lot. The random location choice hypothesis would then not hold for these sectors. To tackle this possible concern, we delete sectors in which the variability of the share of high-level occupations across clusters is high (above 1.5). We choose the share of high-level occupations as criteria as it is known to adequately reflect the social quality of the local environment. The 1.5 threshold corresponds to a clear break in the distribution of the coefficient of variation in the estimation sample. We are left with a sub-sample of 47,833 observations and 2,316 sectors, that is, we loose 12% of the sectors from the initial sample.

Panel B of Table 11 shows the results of our main specification on this new sample. The findings are almost identical to the ones in Table 5. Endogenous effects are positive and significant for all the job search variables, and higher for search through networks than for the other channels. As for the contextual effect, the share of unemployed neighbors previously in low-level occupations still negatively affects total, network and active search. Because the change consists in discarding entire sectors rather than clusters within sectors, identification of group effects is not affected in the same way as when discarding clusters with public housing. The strong negative impact of low-level occupations neighbors on total search, search through networks and active and direct search remains. The slightly significant positive impact of the share of high-level occupations neighbors for search through networks decreases. The most important change is the increase of the coefficient of the share of employed neighbors for search through networks, which translates into an increase also of the impact on total search.

In fine, this robustness check suggests that our results are not affected by the existence of some spatial sorting within heterogenous sectors, and therefore supports the main findings of Section 5.

Table 11: Robustness checks: Discarding public housing clusters and removing heterogenous sectors

	Explained variable			
	Total	Networks	Active	Organizations
	(1)	(2)	(3)	(4)
Panel A: Discarding public housing clusters				
Endogenous effects:				
Un. neighbors' average intensity	0.047***	0.068***	0.051***	0.049***
	(0.006)	(0.006)	(0.006)	(0.006)
Group effects: *non-unemployed neighbors*				
% employed	−0.114	−0.029	−0.108*	0.016
	(0.097)	(0.051)	(0.056)	(0.037)
% low-level occupations	−0.212***	−0.088**	−0.089*	−0.032
	(0.082)	(0.046)	(0.047)	(0.047)
% high-level occupations	−0.008	0.047	−0.059	0.004
	(0.103)	(0.054)	(0.065)	(0.039)
Contextual effects: *unemployed neighbors*				
% ex-low-level occupations	−0.113***	−0.047***	−0.079***	−0.010
	(0.026)	(0.014)	(0.015)	(0.010)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Log-likelihood	-60,149	-40,359	-43,699	-30,941
N (Obs./ Sectors/ Clusters x t/ Indiv.)	32,736 /	2,288 /	20,461 /	15,728
Panel B: Removing heterogenous sectors				
Endogenous effects:				
Un. neighbors' average intensity	0.044***	0.067***	0.048***	0.039***
	(0.005)	(0.005)	(0.005)	(0.005)
Group effects: *non-unemployed neighbors*				
% employed	0.163**	0.113***	0.005	0.034
	(0.076)	(0.039)	(0.044)	(0.029)
% low-level occupations	−0.227***	−0.139***	−0.081**	−0.004
	(0.061)	(0.031)	(0.035)	(0.023)
% high-level occupations	0.031	0.073	−0.011	−0.033
	(0.086)	(0.045)	(0.050)	(0.033)
Contextual effects: *unemployed neighbors*				
% ex-low-level occupations	−0.073**	−0.034***	−0.056***	−0.001
	(0.021)	(0.011)	(0.012)	(0.008)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Log-likelihood	-89,817	-60,066	-65,044	-46,702
N (Obs./ Sectors/ Clusters x t/ Indiv.)	47,833 /	2,316 /	26,835 /	22,496

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

Note: Table 11 presents sector fixed-effects regressions performed on the sample that discards public housing clusters (Panel A) and the sample that removes heterogenous sectors (Panel B). See Table 2 for a detailed presentation of the independent variables.

6.3 Reflection issue

Using the max of neighbors instead of the mean. As explained in Section 4, the reflection issue is encountered in linear models where the measure of endogenous effects is the peers' average. This suggests that a way to circumvent this issue is to consider moments of the distribution of the endogenous effects that are not the mean. Moving away from the linear-in-means model is an emerging literature as in Boucher et al. (2024), who in the framework of a general specification of peer effects, consider using the maximum. In our case, one can imagine that the maximum value of the job search intensity among neighbors could be what influences the individual's job search intensity. Estimating a linear fixed-effects model in which the endogenous effect is the maximum value of neighbors' behavior thus provides a robustness test based on an identification method that differs from our main strategy.[28]

Before going on with the results, it seems important to outline the differences between the interpretation of these two measures of endogenous effects, namely the average and the maximum. While the first endogenous effect shall be understood as a need for conformity to the average behavior (social norm) promoted within the neighborhood, the endogenous effect measured by the maximum shall be more understood as a role model effect according to which the behavior of one individual is affected by the behaviors of "leaders" in the neighborhood. The first effect is reciprocal, while the second occurs through the comparison to the "highest" behavior in the reference group and the need to be "as good as".

Table 12 presents the results with neighbors' top search intensity. In terms of endogenous effect, we find a positive and very significant impact for search through networks for which the magnitude is high, which is then reflected in the endogenous effect for total search. The endogenous effect is also positive and significant for active and direct search, while it is negative and significant at the 5% risk level for search through organizations. As this type of job search channel corresponds to the minimum actions to be taken when unemployed and to the more "official" and traditional ways of seeking for a job, one should not be surprised that it is not driven by role model effects. A high level of job search via this channel is not necessarily seen as a goal to be achieved. Hence, individuals conform to the mean of actions linked to this job search channel in the neighborhood but not to the maximum. This new result supports the idea that it is not the same economic and sociological mechanisms at play when defining the endogenous effect based on average or maximum behavior.

As they are not affected by the reflection issue and therefore the change in the identification strategy, the group effects coefficients and significance are, as expected, very close to the main model for each of the job search variables. As to the contextual effect, the coefficient of the share of unemployed neighbors previously in low-level occupations decreases in absolute value for total, network and active search, and becomes unsignificant. It becomes positive and significant for search through organizations while it was close to zero before. These changes might result from the change in both the measure of the endogenous effect and the estimation method.

Overall, these results head in the same direction as the main results in Table 5, particularly for job search through networks which is the channel the most impacted by social interaction effects. This stability of the results provides some additional support for our empirical strategy to deal with the reflection issue.

[28] Checking the coherence of the implied model is beyond the scope of this paper.

Table 12: Results with top search intensity

	Explained variable			
	Total search	Networks	Active	Organizations
	(1)	(2)	(3)	(4)
Endogenous effects:				
Un. neighbors' top search intensity	0.018***	0.034***	0.017***	−0.011**
	(0.004)	(0.004)	(0.004)	(0.005)
Group effects: *non-unemployed neighbors*				
% employed	0.130*	0.101***	−0.004	0.031
	(0.069)	(0.036)	(0.040)	(0.027)
% low-level occupations	−0.221***	−0.128***	−0.103***	0.013
	(0.055)	(0.028)	(0.032)	(0.021)
% high-level occupations	0.028	0.082*	−0.041	−0.016
	(0.081)	(0.042)	(0.047)	(0.031)
Contextual effects: *unemployed neighbors*				
% ex-low-level occupations	−0.010	−0.017	−0.014	0.024***
	(0.022)	(0.011)	(0.013)	(0.008)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
R^2	0.028	0.033	0.020	0.029
N (Obs./ Sectors/ Clusters x t/ Indiv.)	56,602 /	2,621 /	30,873 /	26,427

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

Note: Table 12 presents linear sector fixed-effects regressions on the estimation sample as defined in the text. The endogenous variables correspond here to the top job search intensity among unemployed neighbors linked to a particular job search channel. See Table 2 for a detailed presentation of the independent variables.

7 Discussion

Data limitations. We have previously outlined that our job search measures have some limits. The best variables for our analysis would have been the time dedicated to each particular job search channel. We are however not aware of any paper with such detailed information. There is in the literature either job search measures with time spent, or regarding the use of one channel vs. others. The important question is whether such a detailed measure, with the two combined dimensions, would give us more insights on neighborhood effects. In the end, the FLFS enables us to observe different channels and to show evidence of neighborhood effects in their use and proxied intensities.

In this paper, we use the clusters of 20 contiguous dwellings as the reference group to study neighborhood effects. The argument supporting this choice is that neighbors in these clusters are sufficiently geographically close to suppose social contacts. It is also, with the FLFS sampling scheme, the lowest geographical level to which we have access to. If we had in the data the exact geolocation of dwellings or, if individuals could report their own set of neighbors, as in some other studies of social interaction effects, we could have tested alternative reference groups. We unfortunately do not, given the data at hand.

Neighborhood size. Although having very small neighborhoods is a good point as it enables us to observe individuals who are likely to interact with each other, a drawback is that we deal with very small numbers of neighbors, especially as it comes to unemployed neighbors characteristics used for contextual effects, and the less frequent categories among unemployed. This is the reason why we opted for not including high-level characteristics of unemployed peers in the contextual effects. This is one limit of our results concerning contextual effects. We are more confident as to the estimated endogenous effects, because the continuous nature of the measures of job search behaviors casts less doubts on their average. For the same reasons, 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. Indeed, the small number of unemployed individuals in each of the cluster calls into question the proper estimation of the corresponding fixed effects.

Time-varying shocks and neighborhood quality changes. With the sector fixed-effects in equation 4.1, we are dealing with correlated effects by comparing unemployed individuals' part of the same sector but not surveyed at the same time i.e. over possibly 5 years. This means that we use as control group unemployed individuals who live in the same sector but at different times, which raises the following question: could there be local time-varying shocks that would affect clusters' unobservables, or yield some sorting of individuals across clusters within sectors over time? Examples of time-varying local shocks that could affect unobservables could be the closure of a local French Employment Agency (Pôle Emploi) that could lead to less search via official back-to-work official agencies in a neighborhood. All individuals in a neighborhood would be simultaneously affected, creating a correlation in their behaviors. If this happened, the sector fixed-effects, which do not capture the time-varying components, would not control anymore correctly for unobservables, which would create a bias in the estimated neighborhood effects. To affect the results, these type of shocks would nonetheless have to be frequent in the sample, which is highly unlikely. Other time-varying shocks could affect the type of individuals who locate in the sector, and its different clusters over time, thus creating some sorting, and inadequate control groups. Examples of these type of shocks could be social housing construction or changes in access to transportation within the sector. Our robustness check that removes heterogeneous sectors is a piece of evidence against this potential limit. By removing sectors for which we observe high variation of socio-economic characteristics across clusters, we withdraw sectors which might have experienced a social composition evolution over time, and see that our main results still hold. Our robustness check that includes a network formation model might also control the potential sorting consequences related to these time-varying shocks. By controlling for the unobservables linked to the choice of living in one cluster vs. another one in the same sector, this specification allows to control for a potential change in time of unobservable characteristics across clusters.

8 Conclusion

This paper aims at detecting and measuring the importance of interactions with neighbors in the job search behaviors of unemployed individuals, which we know, play a central role in return to employment and labor market outcomes. We use data from the FLFS that allows us to (i) identify three job search channels, namely search through employment organizations, search through active and direct actions and search through networks and build measures of search intensity, and (ii) identify two nested levels of neighborhoods at a very thin and precise level, through the existence of clusters of 20 contiguous dwellings grouped into sectors.

We delve into the questions of social interactions through the implementation of a model of endogenous (how the average behavior of neighbors impacts individual behavior), contextual and group effects (how neighbors' characteristics impact individual behavior) à la Manski (1993), applied to the three job search channels and total search. We tackle the reflection issue that threatens the separate econometric identification of endogenous and contextual effects following

Lee (2007) and the development provided in Boucher et al. (2014) through the use of exclusive averaging and group size variations. We control for the non-random sorting of individuals into neighborhoods in a similar way as in Bayer et al. (2008), with the inclusion of sector fixed-effects, assuming that once controlled for a higher level of location, the sector, location within clusters can be considered as exogenous. We conduct a series of robustness checks to support these two elements of our identification strategy.

We contribute to the literature by giving evidence of the presence of neighborhood effects in job search behaviors. We find important endogenous effects for the three job search channels we consider and for total search intensity. Such 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. These are particularly strong for search through networks. A one standard deviation increase in the endogenous effect increases, with regards to mean search intensity, this type of job search by 5.4% against 2.5% and 3.4% respectively for active and direct search, and search through organizations. These effects can either be explained by social pressure in non-deviating from the job search behaviors promoted within the neighborhood or through a spread of information between peers that reduces the costs associated to job search. Our heterogeneity analysis underlines that these effects seem to be stronger in denser environments. We also estimate a specification in which the endogenous effect is the maximum behavior. The change in results for search through organizations is consistent with the nature of this type of job search. As it corresponds to the minimum actions to be taken when unemployed and to the most traditional way of job-seeking, one should not be surprised that it is not driven by role model effects. We also find some contextual and group effects with regards to neighbors' labor market status and occupations for total search intensity, active and direct search, and search through networks. They mainly highlight that interactions with neighbors highly connected to the labor market are important regarding access to information on job opportunities.

The public policy implications of our findings depend on the prevalence of the different social interaction effects. The results with regards to the endogenous effect variables seem to win both in terms of significance and magnitude in our main specification and across the different models and robustness checks. Moreover, the change in the share of high-level occupations in the local neighborhood needed to increase job search intensity would require a strong shift in the quality of the neighborhood whereas the increase needed in the search intensity of unemployed neighbors to see a significant change in the person's search intensity seems more plausible. 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), 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.

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. Further research would require to evaluate the role played by these job search neighborhood effects in unemployment exit. Moreover, the strong social interactions results for search through networks can be connected to the literature underlining the higher efficiency of this channel (Montgomery, 1991;

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 mechanisms behind the neighborhood effects that we find. Further research is needed to know the relative contributions of social pressure, spread of information, imitation.

The social interactions results for search through networks channel also seem important to discuss the potential public policy implications of our findings. On the one hand, the existence of imitation effects implies that a counselling policy favouring job search via networks among the unemployed would amplify, through the social multiplier effect, the use of this channel which could lead to a faster return to the labor market. On the other hand, the results linked to contextual effects (favourable effect of the share of high-level occupations) seem to be in favour of social diversity, and of policies that imply a real shift in the quality of the neighborhood, such as the Solidarity and Urban Renewal Act (*loi Solidarité et Renouvellement urbain*, SRU) in France or the Moving To Opportunity (MTO) program in the United States.

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Appendices

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 Distribution of neighbors by characteristics in the estimation sample

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

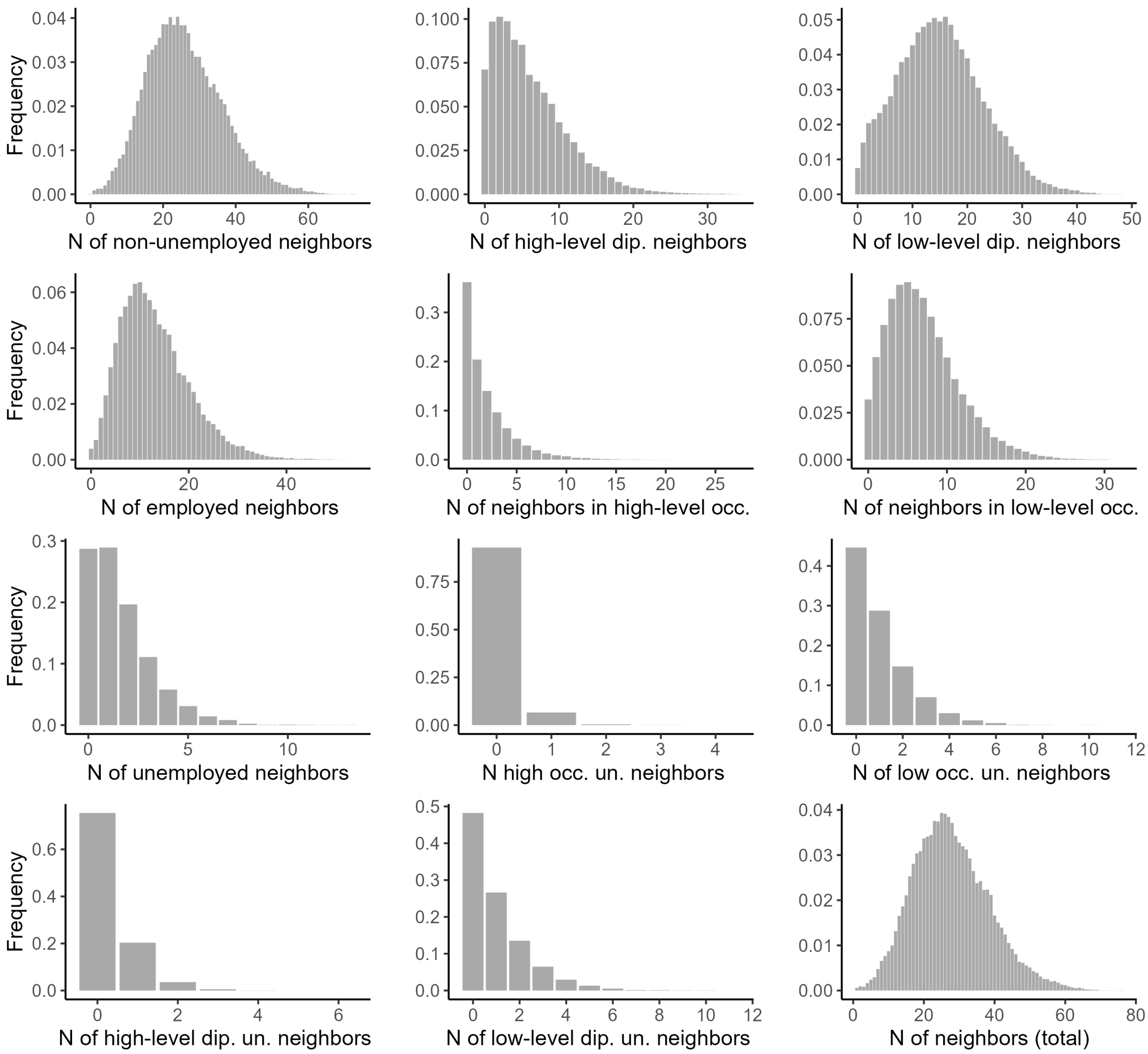


Figure B.1 displays the distribution of neighbors by characteristics in the estimation sample. In the first row, we find the distribution of the number of non-unemployed neighbors and among them, how many have high-level or low-level diplomas. In the second row, we have the number of employed neighbors,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

Comments: Unsurprisingly, the number of neighbors in high-level occupations is in general much lower than that of neighbors in low-level occupations. The distribution of the number of neighbors with high-level diplomas is more spread than that of high-level occupations, with a more sizable fraction of individuals having more than 10 neighbors with high-level diploma, while that of low-level diplomas is comparable to that of low-level occupations neighors. The number of unemployed neighbors vary between 0 and 13: 28.7% of observations have no unemployed neighbors, while 28.9% have one, 19.7% have two, 16.9% have three or four and 5.8% have more than four unemployed neighbors. With regards to the characteristics of these unemployed neighbors, we observe that in 93% of cases there is no unemployed neighbors previously in high-level occupations, while the number of unemployed neighbors previously in low-level occupations varies more across the sample. Having unemployed neighbors with high-level diplomas is a bit less scarce than for ex-high-level occupations but still very low. The number of unemployed neighbors with low-level diplomas takes higher values than that of high-level diplomas, and exhibits a less scattered distribution than that of ex-low-level occupations unemployed neighbors.

C Distribution of endogenous, contextual and group effects

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

	Min	Q1	Median	Q3	Max	Mean	SD
Endogenous effects	*Un. neighbors' average intensity*						
Total	0	0	3	4.5	10	2.86	2.25
Networks	0	0	1	1.5	3	0.89	0.92
Active	0	0	1.5	2.3	5	1.43	1.18
Organizations	0	0	0.5	1	2	0.54	0.59
Contextual effects	*among unemployed neighbors*						
% low-level diploma	0	0	0.33	1	1	0.41	0.43
% high-level diploma	0	0	0	0	1	0.15	0.31
% low-level occupations	0	0	0.50	1	1	0.44	0.44
% high-level occupations	0	0	0	0	1	0.04	0.18
Group effects							
Among non-unemployed neighbors							
% employed	0	0.39	0.50	0.61	1.00	0.47	0.16
% low-level diploma	0	0.45	0.60	0.73	1.00	0.58	0.21
% high-level diploma	0	0.11	0.20	0.33	1.00	0.24	0.18
Among employed neighbors							
% low-level occupations	0	0.38	0.56	0.75	1.00	0.55	0.26
% high-level occupations	0	0	0.09	0.22	1.00	0.15	0.18
Estimation sample	56,602 obs. / 2,621 sectors / 30,873 gxt / 26,427 indiv.						

Table C.2: Decile distribution of endogenous, contextual and group effect variables

	D1	D2	D3	D4	D5	D6	D7	D8	D9
	10%	20%	30%	40%	50%	60%	70%	80%	90%
Endogenous effects	*Un. neighbors' average intensity*								
Total	0	0	1	2.50	3	3.67	4	5	6
Networks	0	0	0	0.25	1	1	1.33	2	2
Active	0	0	0	1	1.50	2	2	2.50	3
Organizations	0	0	0	0	0.50	0.67	1	1	1.33
Contextual effects	*among unemployed neighbors*								
% low-level diploma	0	0	0	0	0.33	0.50	0.75	1	1
% high-level diploma	0	0	0	0	0	0	0	0.33	0.67
% low-level occupations	0	0	0	0	0.50	0.60	1	1	1
% high-level occupations	0	0	0	0	0	0	0	0	0
Group effects									
among non-unemployed neighbors									
% employed	0.29	0.36	0.42	0.46	0.50	0.54	0.58	0.63	0.70
% low-level diploma	0.29	0.41	0.49	0.55	0.60	0.65	0.70	0.76	0.833
% high-level diploma	0.04	0.08	0.13	0.17	0.20	0.25	0.30	0.38	0.50
among employed neighbors									
% low-level occupations	0.20	0.33	0.41	0.50	0.56	0.63	0.70	0.79	0.89
% high-level occupations	0	0	0	0.06	0.09	0.13	0.19	0.26	0.40
Estimation sample	56,602 obs. / 2,621 sectors / 30,873 gxt / 26,427 indiv.								

* Tables C.1 and C.2 show the distribution of endogenous, contextual and group effects on the estimation sample.

D Specification with diploma

Table D.1: Specification with diploma

	Explained variable			
	Total	Networks	Active	Organizations
	(1)	(2)	(3)	(4)
Endogenous effects:				
Un. neighbors' average intensity	0.047***	0.072***	0.049***	0.043***
	(0.004)	(0.004)	(0.004)	(0.004)
Group effects: *non-unemployed neighbors*				
% employed	0.038	0.039	−0.043	0.032
	(0.073)	(0.038)	(0.014)	(0.028)
% low-level diploma	−0.035	0.026	−0.067	0.008
	(0.100)	(0.052)	(0.058)	(0.038)
% high-level diploma	0.153	0.224***	−0.029	−0.040
	(0.115)	(0.060)	(0.067)	(0.045)
Contextual effects: *unemployed neighbors*				
% low-level diploma	−0.061***	−0.034***	−0.035***	−0.007
	(0.020)	(0.011)	(0.012)	(0.008)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Log-likelihood	-106,553	-71,323	-77,048	-55,484
N (Obs./ Sectors/ Clusters x t/ Indiv.)	56,602	/ 2,621	/ 30,873	/ 26,427

Note: *p<0.1; **p<0.05; ***p<0.01

Table D.1 presents sector fixed-effects regressions performed on the estimation sample as defined in the text. See Table 2 for a detailed presentation of the independent variables.

Table D.2: Magnitudes of social interaction effects - Specification with diploma

	Total	Networks	Active	Organizations
Endogenous effects:				
Un. neighbors' average intensity	+2.62%	+5.18%	+2.88%	+3.43%
Group effects: *non-unemployed neighbors*				
% employed	NS	NS	NS	NS%
% low-level diploma	NS	NS	NS	NS
% high-level diploma	NS	+3.2%	NS	NS%
Contextual effects: *unemployed neighbors*				
% low-level diploma	−0.6%	−1.2%	−0.9%	NS
Mean of JS variables	4.03	1.28	2.01	0.75
s.d of JS variables	1.88	1.01	1.07	0.71

Table D.2 presents the magnitudes of the effects of the coefficients of regressions in Table D.1. Reading direction: a 1 s.d increase in explanatory variables increases search intensity by % (with regards to mean intensity). See Table 2 for a detailed presentation of the independent variables.

E Control variables: main and second specification

Table E.1: Control variables - main and second specification

	Total		Networks		Active		Organizations	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Endogenous effects: *unemployed neighbors*								
Av. search intensity	0.049***	0.047***	0.074***	0.072***	0.051***	0.049***	0.043***	0.043***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Group effects: *non-unemployed neighbors*								
% employed	0.107	0.038	0.091**	0.039	−0.017	−0.043	0.023	0.032
	(0.069)	(0.073	(0.036)	(0.038)	(0.040)	(0.014)	(0.027)	(0.028)
% low-level occ./ dipl.	−0.217***	−0.035	−0.121***	0.026	−0.101***	−0.067	0.009	0.008
	(0.055)	(0.100)	(0.028)	(0.052)	(0.032)	(0.058)	(0.021)	(0.038)
% high-level occ./ dipl.	0.028	0.153	0.078*	0.224***	−0.039	−0.029	−0.013	−0.040
	(0.081)	(0.115)	(0.042)	(0.060)	(0.047)	(0.067)	(0.031)	(0.045)
Contextual effects: *unemployed neighbors*								
% ex-low occ. / dipl.	−0.080***	−0.061***	−0.041***	−0.034***	−0.053***	−0.035***	−0.004	−0.007
	(0.020)	(0.020)	(0.010)	(0.011)	(0.011)	(0.012)	(0.008)	(0.008)
Previous occupation								
Low-level occupation	−0.215***		−0.210***		−0.052***		0.045***	
	(0.021)		(0.012)		(0.012)		(0.008)	
Other occupation	Ref.		Ref.		Ref.		Ref.	
High-level occupation	0.303***		0.337***		0.037*		−0.070***	
	(0.036)		(0.019)		(0.021)		(0.014)	
Has never worked	−0.573***		−0.369***		−0.132***		−0.072***	
	(0.031)		(0.016)		(0.012)			
Education								
Low-level diploma		−0.288***		−0.138***		−0.138***		−0.012
		(0.021)		(0.011)		(0.012)		(0.008)
Gen./Prof. baccalaureate		Ref.		Ref.		Ref.		Ref.
High-level diploma		0.204***		0.198***		0.048***		−0.042***
		(0.024)		(0.013)		(0.013)		(0.009)
Age								
15-29	0.296***	0.124***	0.069***	−0.032***	0.173***	0.129***	0.053***	0.027***
	(0.025)	(0.024)	(0.013)	(0.013)	(0.014)	(0.014)	(0.009)	(0.009)
30-39	0.047**	0.005	0.014	−0.014	0.032**	0.018	0.001	0.001
	(0.024)	(0.024)	(0.012)	(0.012)	(0.014)	(0.014)	(0.009)	(0.009)
40-49	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
50-59	−0.247***	−0.199***	−0.051***	−0.021	−0.096***	−0.079***	−0.099***	−0.099***
	(0.025)	(0.025)	(0.013)	(0.013)	(0.015)	(0.015)	(0.009)	(0.009)
Above 60	−0.605***	−0.537***	−0.109***	−0.057**	−0.280***	−0.262***	−0.215***	−0.217***
	(0.044)	(0.044)	(0.023)	(0.023)	(0.026)	(0.026)	(0.017)	(0.017)
Sex (female)	−0.195***	−0.262***	−0.081***	−0.129***	0.058***	0.037***	−0.173***	−0.171***
	(0.016)	(0.016)	(0.008)	(0.008)	(0.009)	(0.009)	(0.006)	(0.006)
Child (0/1)	−0.038*	0.002	0.021**	0.046***	−0.033***	−0.021*	−0.027***	−0.023***
	(0.020)	(0.020)	(0.011)	(0.011)	(0.012)	(0.012)	(0.008)	(0.008)
Foreigner (0/1)	−0.073***	−0.117***	−0.001	−0.036**	−0.129***	−0.139***	0.057***	0.056***
	(0.026)	(0.026)	(0.013)	(0.013)	(0.015)	(0.015)	(0.010)	
Partner's status								
Employed partner	0.016	0.037*	0.035***	0.054***	−0.001	−0.001	−0.018**	−0.014*
	(0.021)	(0.021)	(0.011)	(0.011)	(0.012)	(0.012)	(0.008)	(0.008)
Unemployed partner	−0.028	−0.001	−0.002	0.017	−0.003	0.004	−0.025	−0.023
	(0.046)	(0.046)	(0.024)	(0.024)	(0.027)	(0.027)	(0.017)	(0.017)
No partner	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Inactive partner	−0.181***	−0.146***	−0.036**	−0.016	−0.122***	−0.112***	−0.023**	−0.017
	(0.028)	(0.028)	(0.015)	(0.015)	(0.016)	(0.016)	(0.011)	(0.011)
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-106,552	-106,553	-71,093	-71,323	-77,138	-77,048	-55,388	-55,484
N (Obs./ Sectors/ g x t)			56,602 / 2,621 / 30,873 / 26,427					
Note:								*p<0.1; **p<0.05; ***p<0.01

Table E.1 presents sector fixed-effects regressions performed on the estimation sample as defined in the text. Model (1) corresponds to the specification with occupations, while model (2) corresponds to the specification with diplomas. See Tables 1 and 2 for a detailed presentation of the independent variables.

Table E.2: Magnitudes of individual effects - main specification

	Total	Networks	Active	Organizations
Ex-occupations:				
ex-low-level occupations	+1.7 %	−2.8%	NS	+14.7%
ex-intermediate occupations	Ref.	Ref.	Ref.	Ref.
ex-high-level occupations	+14.75%	+35.38%	+7.9%	−6.7%
Nationality:				
Foreigner	−3.7 %	−1.15%	−8.9%	+6.7%
French	Ref.	Ref.	Ref.	Ref.
Age:				
15-29	+3.4 %	−1.5%	+6.8%	+6.7%
30-39	NS %	NS	+3.0%	NS
40-49	Ref.	Ref.	Ref.	Ref.
50-59	−7.0%	−3.1%	−6.8%	−13.3%
Above 60	−21 %	−10%	−22.6%	−30.6%
Sex:				
Female	−5.4 %	−5.4%	+3.5%	−2.6%
Male	Ref.	Ref.	Ref.	Ref.
Child:				
Having a child or more	−1 %	+1.7%	−2.5%	−5.1%
No child	Ref.	Ref.	Ref.	Ref.
Mean of JS variables	4	1.3	1.9	0.75
s.d of JS variables	2.23	1.14	1.18	0.78

Table E.2 presents the magnitudes of the effects implied by the coefficients of the regressions of the main specification in Table E.1. Reading direction: Being of an ex-high-level occupation compared to an intermediate occupation increases total search intensity by 14.75% (with regards to mean intensity). See Table 1 for a detailed presentation of the independent variables.

F Horse race test for the network endogenous effect

Table F.1: Horse race exercise - Main specification

	Explained variable: Search through networks			
	(1)	(2)	(3)	(4)
Endogenous effects:				
Un. neighbors' average intensity	0.070***	0.075***	0.070***	0.074***
	(0.004)	(0.004)	(0.004)	(0.004)
Contextual effects: *unemployed neighbors*				
% ex-low-level occ.		−0.047***		−0.041***
		(0.010)		(0.010)
Group effects: *non-unemployed neighbors*				
% employed			0.089**	0.091**
			(0.035)	(0.035)
% low-level occupations			−0.127***	−0.121***
			(0.028)	(0.028)
% high-level occupations			0.086**	0.078*
			(0.042)	(0.042)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Log-likelihood	-71125.50	-71115.59	-71100.62	-71093.12
N (Obs./ Sectors/ Clusters x t/ Indiv.)	56,602 /	2,621 /	30,873 /	26,427
Note:				*p<0.1; **p<0.05; ***p<0.01

Table F.2: Horse race exercise - Second specification

	Explained variable: Search through networks			
	(1)	(2)	(3)	(4)
Endogenous effects:				
Un. neighbors' average intensity	0.070***	0.073***	0.070***	0.072***
	(0.004)	(0.004)	(0.004)	(0.004)
Contextual effects: *unemployed neighbors*				
% low-level diploma		−0.038***		−0.034***
		(0.010)		(0.010)
Group effects: *non-unemployed neighbors*				
% employed			0.036	0.036
			(0.038)	(0.038)
% low-level diploma			0.020	0.026
			(0.052)	(0.052)
% high-level diploma			0.230***	0.224***
			(0.060)	(0.060)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Log-likelihood	-71343.68	-71337.50	-71327.96	-71323.15
N (Obs./ Sectors/ Clusters x t/ Indiv.)	56,602 /	2,621 /	30,873 /	26,427
Note:				*p<0.1; **p<0.05; ***p<0.01

Tables F.1 and F.2 present sector fixed-effects horse race regressions performed on the estimation sample as defined in the text. See Table 2 for a detailed presentation of the independent variables.

G Comparing dense to non dense sectors

Table G.1: Regression results for dense areas

	Explained variable			
	Total	Networks	Active	Organizations
	(1)	(2)	(3)	(4)
Endogenous effects				
Un. neighbors' average intensity	0.069***	0.100***	0.065***	0.050***
	(0.007)	(0.007)	(0.007)	(0.007)
Group effects *(among non-unemp. neighb.)*				
% employed	0.235**	0.127**	0.025	0.075*
	(0.112)	(0.057)	(0.065)	(0.024)
% low-level occupations	−0.223**	−0.133***	−0.055	−0.028
	(0.080)	(0.046)	(0.052)	(0.034)
% high-level occupations	−0.101	0.021	−0.016	−0.109**
	(0.127)	(0.065)	(0.075)	(0.049)
Contextual effects *(among unemp. neighb.)*				
% ex-low-level occupations	−0.131***	−0.059***	−0.068***	−0.014
	(0.036)	(0.018)	(0.021)	(0.014)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Log-likelihood	-35,864	-23,763	-26,155	-18,584
N (Obs./ Sectors/ Clusters x t/ Indiv.)	18,920	/ 786	/ 9,373	/ 8,768

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

Note: See Table 2 for a detailed presentation of the independent variables.

Table G.2: Regression results for non dense areas

	Explained variable			
	Total	Networks	Active	Organizations
	(1)	(2)	(3)	(4)
Endogenous effects				
Un. neighbors' average intensity	0.039***	0.060***	0.044***	0.040***
	(0.005)	(0.005)	(0.005)	(0.005)
Group effects *(among non-unemp. neighb.)*				
% employed	0.028	0.068	0.042	−0.008
	(0.088)	(0.045)	(0.051)	(0.034)
% low-level occupations	−0.199***	−0.113***	−0.123***	0.038
	(0.080)	(0.036)	(0.040)	(0.026)
% high-level occupations	0.115	0.109**	−0.055	0.060
	(0.105)	(0.055)	(0.061)	(0.041)
Contextual effects *(among unemp. neighb.)*				
% ex-low-level occupations	−0.055**	−0.032***	−0.045***	0.0009
	(0.036)	(0.012)	(0.014)	(0.009)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Log-likelihood	-70,626	-47,272	-50,928	-36,764
N (Obs./ Sectors/ Clusters x t/ Indiv.)	37,671	/ 1,834	/ 21,494	/ 17,652

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

Note: See Table 2 for a detailed presentation of the independent variables.

Table G.3: Magnitudes of social interaction effects - dense sectors

	Impacts for 1 s.d. in the dependent variable			
	Total (1)	Networks (2)	Active (3)	Organizations (4)
Endogenous effects:				
Un. neighbors' average intensity	+3.7%	+6.8%	+3.8 %	+3.9%
Group effects: *non-unemployed neighbors*				
% employed	+1.1%	+1.8%	NS	+1.8%
% low-level occupations	−1.6%	−2.9%	NS	NS
% high-level occupations	NS	NS	NS	−3.2%
Contextual effects: *unemployed neighbors*				
% ex-low-level occupations	−1.4%	−1.9%	−1.5%	NS
Mean of JS variables	4.03	1.33	1.96	0.74
s.d of JS variables	1.90	1.01	1.09	0.71

Table G.3 presents the magnitudes of the effects of the estimated coefficients in Table G.1. Reading direction: a 1 s.d increase in the average total search intensity of unemployed neighbors increases total search by 3.7% (with regards to mean intensity).

Table G.4: Magnitudes of social interaction effects - non dense sectors

	Impacts for 1 s.d. in the dependent variable			
	Total (1)	Networks (2)	Active (3)	Organizations (4)
Endogenous effects:				
Un. neighbors' average intensity	+2.2%	+4.4%	+2.6 %	+3.2%
Group effects: *non-unemployed neighbors*				
% employed	NS	NS	NS	NS
% low-level occupations	−1.1%	−2.1%	−1.4%	NS
% high-level occupations	NS	NS	NS	NS
Contextual effects: *unemployed neighbors*				
% ex-low-level occupations	−0.6%	−1.1%	−0.9%	NS
Mean of JS variables	4.01	1.25	2.03	0.75
s.d of JS variables	1.87	1.00	1.06	0.71

Table G.4 presents the magnitudes of the effects of the estimated coefficients in Table G.2. Reading direction: a 1 s.d increase in the average total search intensity of unemployed neighbors increases total search by 2.2% (with regards to mean intensity).

H Characteristics of unemployed on different samples

Table H.1: Descriptive statistics (in %): individuals alone vs. not alone

	Alone %	Not alone %
Age		
Age 15+	36.4	38.3
Age 30+	20.7	22.5
Age 40+	19.6	19.3
Age 50+	19	16.5
Age 60+	4.3	3.5
Female	48.9	48.9
Has one child or more	36.2	39.4
Nationality		
French	90.2	87.1
Foreigner	9.8	12.9
Education [a]		
High-level diploma	29.9	23.3
Baccalaureate	22.9	21.9
Low-level diploma	46.6	54.5
Missing	0.6	0.4
Previous occupation [a]		
Farmers	0.1	0.1
Independent workers	2.8	2.6
High-level occupations	9.1	6.2
Intermediate occupations	16.4	13.6
Low-level occupations	55.6	59.3
Unemployed (have never worked)	15.1	17.5
Missing	1.0	0.7
Dwelling's architectural environment [b]		
Scattered houses outside of urban agglomerations	11.4	8.6
Houses in an urban or sub-urban environment	42.1	34.8
Flats in high-rise housing projects	11.3	27.6
Other flats in urban areas	29.7	23.4
Mixed housing	5.5	5.8
Type of area [c]		
Rural municipalities[c]	17.2	13.3
Urb. unit < 10,000 inhabitants	8.9	7.4
Urb. unit 10,000 to 50,000 inhab.	9.6	10.4
Urb. unit 50,000 to 100,000 inhab.	8.5	9.1
Urb.unit 100,000 to 200,000 inhab.	6.6	8.1
Urb. unit > 200,000 inhab. (except Paris)	31.0	34.9
Paris urban unit	18.3	16.8
N individuals	10,311	20,831

Table H.1 shows the individual characteristics of unemployed present on two sub-samples derived from the main sample. The first includes all individuals who have been alone (i.e. without unemployed neighbors) in their cluster at some point within the 6 quarters of observation. The second one comprises all individuals who have had unemployed neighbors in their cluster at some point within the 6 quarters of observation. Some individuals within their 6 quarters of analysis can be found (at different date) with both no unemployed neighbors, and with unemployed neighbors. It is the case of 4,715 individuals.

[a] For a definition of education and occupations, see Table 1.

[b] Architectural environment: Scattered houses outside of urban agglomerations(UA) refer to the French "*Maisons dispersées, hors agglomération*"; Houses in an (sub-)urban environment refer to "*Maison en lotissement, en quartier pavillonnaire ou en ville*" ; Flats in urban areas to "*Immeubles en ville autres que cité ou grand ensemble*"; Flats in high-rise housing projects to "*Immeubles en cité ou grand ensemble*"; Mixed housing is a mix of houses and buildings.

[c] Rural municipalities in the sample are municipalities below 2000 inhabitants part of an urban area. See note 5 for the definition of urban areas.

Table H.2: Descriptive statistics (in %): individuals present in different samples

	A	B	B bis	C	D	E
	%	%	%	%	%	%
Age						
Age 15+	39.0	39.5	38.1	38.9	37.5	39.1
Age 30+	21.9	20.7	23.6	22.0	24.1	20.8
Age 40+	19.1	18.6	19.9	19.0	19.7	18.9
Age 50+	16.5	17.1	15.5	16.4	15.2	17.2
Age 60+	3.6	4.0	2.9	3.6	3.5	4.0
Female	49.2	49.5	48.8	49.2	47.7	50.0
Has one child or more	38.6	35.1	43.8	38.1	39.0	38.3
Nationality						
French	87.9	91.6	82.6	88.8	77.9	92.9
Foreigner	12.1	8.4	17.4	11.2	22.1	7.1
Education [a]						
High-level diploma	25.1	30.7	16.7	26.8	27.1	24.0
Baccalaureate	22.5	24.3	19.9	22.9	19.8	23.8
Low-level diploma	52.0	44.7	62.9	49.9	52.1	51.7
Missing	0.4	0.3	0.5	0.4	0.9	0.9
Previous occupation [a]						
Farmers	0.1	0.1	0.1	0.1	0.1	0.1
Independent workers	2.7	3.0	2.2	2.7	2.8	2.6
High-level occupations	6.9	9.3	3.4	7.8	8.2	6.3
Intermediate occupations	14.2	17.1	10.0	15.0	12.8	14.9
Low-level occupations	57.7	53.2	64.2	56.4	57.3	58.5
Unemployed (have never worked)	17.6	16.4	19.4	17.3	17.7	16.7
Missing	0.8	0.8	0.7	0.8	1.0	0.8
Dwelling's architectural environment [b]						
Scattered houses outside of urb. agglomerations	9.4	13.8	2.9	10.0	0.6	13.7
Houses in an urban or sub-urban environment	36.7	46.5	22.3	38.6	2.2	53.9
Flats in high-rise housing projects	20.3	4.9	42.9	16.7	44.5	8.3
Other flats in urban areas	28.0	29.3	26.0	29.1	51.8	16.1
Mixed housing	5.6	5.4	6.0	5.6	1.0	8.0
Type of area						
Rural municipalities[c]	14.3	20.2	5.6	15.3	0.5	21.4
Urb. unit < 10,000 inhabitants	7.7	9.6	4.8	8.1	5.7	11.2
Urb. unit 10,000 to 50,000 inhab.	10.3	9.9	10.7	9.7	9.3	12.5
Urb. unit 50,000 to 100,000 inhab.	8.9	7.5	11.1	8.1	8.5	8.8
Urb.unit 100,000 to 200,000 inhab.	7.7	6.1	10.1	7.3	41.4	7.3
Urb. unit > 200,000 inhab. (except Paris)	33.8	31.7	36.9	34.3	34.6	30.1
Paris urban unit	17.3	14.9	20.8	17.3	8.7	
N individuals	26,427	15,728	10,699	22,496	8,768	17,652

Table H.2 shows the individual characteristics of unemployed present on 5 different samples: *A* the estimation sample; *B* discards social housing clusters; *B bis* comprises unemployed present in the discarded social housing clusters from the previous sample; *C* removes heterogeneous sectors in terms of % high-level occupations; *D* comprises dense sectors; *E* is made of non-dense sectors.

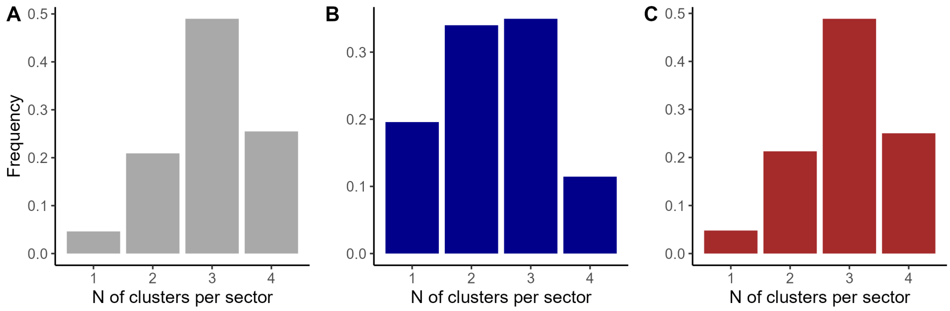
[a] For a definition of education and occupations, see Table 1.

[b] Architectural environment: Scattered houses outside of urban agglomerations(UA) refer to the French "*Maisons dispersées, hors agglomération*"; Houses in an (sub-)urban environment refer to "*Maison en lotissement, en quartier pavillonnaire ou en ville*" ; Flats in urban areas to "*Immeubles en ville autres que cité ou grand ensemble*"; Flats in high-rise housing projects to "*Immeubles en cité ou grand ensemble*"; Mixed housing is a mix of houses and buildings.

[c] Rural municipalities in the sample are municipalities below 2000 inhabitants part of an urban area. See note 5 for the definition of urban areas.

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

Figure I.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 I.1: Number of individuals by characteristics in the clusters x quarter - Estimation sample

	Min	Q1	Median	Q3	Max	Mean	SD
# individuals	2	21	28	36	78	28.81	10.95
# unemployed	1	1	1	2	14	1.83	1.18
# unemp. low diploma	0	0	1	1	11	0.99	1.09
# unemp. high diploma	0	0	0	1	7	0.44	0.63
# unemp. low occupations	0	0	1	2	11	1.11	1.06
# unemp. high occupations	0	0	0	0	4	0.13	0.36
# non-unemployed	0	19	26	34	75	26.75	10.77
# non-unemp. low diploma	0	3	6	10	35	6.91	5.19
# non-unemp. high diploma	0	9	15	20	49	14.89	7.96
# employed	0	8	13	18	54	13.65	7.29
# employed low occupations	0	0	1	3	27	2.34	2.75
# employed high occupations	0	3	6	9	32	6.81	4.60
N cluster x quarter				30,873			

This table describes the distribution of the number of all, unemployed, non-unemployed, and employed individuals by characteristics for the 30,873 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 1.