Neighbourhood effects and Job search behaviours

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Abstract

This paper aims to test for the influence of interactions with neighbours on the job search behaviours of unemployed individuals. Using data from the 2014-2019 French Labour Force Surveys (INSEE) that allows to identify two nested levels of very precise neighbourhoods, we implement a model of endogenous (how the average behaviour of neighbours impacts individual's behaviour) and contextual effects (how neighbours' characteristics impact individual's behaviour) à la Manski (1993) applied to different job search methods and intensity. We control for location endogeneity in a similar way as in Bayer, Ross and Topa (2008) and tackle the reflection issue through the use of non-linear estimation techniques and specific computational methods for the social interaction variables. We find evidence of endogenous peer effects for most of the job search methods with a negative impact of having unemployed neighbours counterbalanced by a strong positive effect of their search intensity. We also find some contextual effects with regards to the share of neighbours in high-level occupations for total search intensity and search through networks. These results underline the importance of having neighbours highly connected to the labour market in return to employment and suggest that social interaction effects regarding job search could amplify labour market inequalities across neighbourhoods.

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1 Introduction

The main motivation for this research lies in the existence of strong differences in unemployment rates across neighbourhoods in cities. For instance, French deprived neighbourhoods face an unemployment rate two and a half time higher than other places in France: 22.5% against 8.4% in 2020 (ONPV, 2020).[1] A first obvious explanation to these differences is residential sorting while additional mechanisms might reinforce such inequalities.

Several studies have shown the importance of interactions with neighbours on labour-market related outcomes. In particular, the neighbourhood effects literature underlines the existence of peer effects in behaviours such as attitudes towards work (Akerlof, 1980; Wilson, 1987; Crane, 1991; Cutler and Glaeser, 1997) or human capital acquisition (Arnott and Rowse, 1987; Benabou, 1993; Evans et al., 1992; Goux and Maurin, 2005, 2007; Del Bello et al., 2015). It also stresses the importance of interactions with employed neighbours in access to information on job opportunities and in creation of networks that facilitate a return to employment, especially if these neighbours are in high-level occupations (Bayer et al., 2008; Topa and Zenou, 2015; Hellerstein et al., 2011, 2014; Schmutte, 2015). Such effects could amplify labour market inequalities across neighbourhoods.

Another body of literature tells us that job search is important for return to employment and for example that the job search channels used, and more particularly formal methods which are more costly or informal methods (professional or personal contacts, social media) which are less time-consuming, induce different types of equilibrium in terms of unemployment duration (Merlino, 2014; Stupnytska and Zaharieva, 2015). In addition, the literature on urban search models underlines that one of the central mechanisms that can explain spatial inequalities in labour market outcomes is search intensity, which decreases with distance to jobs, and results in higher unemployment risks on city outskirts. This relationship is attributed to a lower cost of remaining unemployed with lower housing costs when living far from the employment centre (Zenou, 2009).

One question consequently emerges: could neighbourhood effects in job search behaviours be involved in the existence and persistence of urban unemployment inequalities? Trying to answer this question is all the more important as, to the exception of Patacchini and Zenou (2005, 2006), there has been very few papers targeting spatial differences in job search behaviours.

This paper aims to fill this gap by analysing how job search behaviours of unemployed individuals, both in terms of job search channels and search intensity, are influenced by interactions with neighbours. To that end, we use data from the French Labour Force Survey (*Enquête Emploi*) of the French National Institute for Statistics and Economic Studies (*Institut national de la statistique et des études économiques*, INSEE) that allows us to:

(i) Identify *different job search channels* including search through employment organisations, search through active and direct actions and search through networks, at the individual level.

(ii) Identify two nested levels of neighbourhoods at a very fine and precise level, with the existence of clusters of 20 contiguous dwellings, where daily interactions between residents can be assumed, grouped into sectors.

We delve into these questions of social interactions with a model à la Manski (1993) of endoge-

[1] French deprived neighbourhoods correspond here to Priority Zones (QP, *Quartiers Prioritaires*) defined as policy targets in the French urban policy. They identify urban areas with a high concentration of low-income population.

nous (how the average behaviour of neighbours impacts individual behaviour) and contextual effects (how neighbours' characteristics impact individual behaviour) applied to three different job search channels and to total search intensity. We deal with the reflection issue, which captures the problem of disentangling endogenous effects from contextual effects, with the use of a non-linear econometric model and specific computational methods of endogenous and contextual effects. To tackle the location endogeneity issue, which relates to the non-random sorting of individuals into neighbourhoods, we follow Bayer et al. (2008) and use a method that assumes that location within clusters can be considered as exogenous conditional on a larger location level (groups of contiguous clusters).

Our results show the existence of neighbourhood effects in job search behaviours. We find important endogenous effects for two out of the three job search channels we consider and for total search intensity. We underline a simultaneous negative impact on unemployed individuals' search intensity of having unemployed neighbours, offset by a strong positive effect of their search intensity. Such findings suggest the existence of peer effects in the use of a particular job search channel and the related intensity, the relying mechanisms being both in terms of perception of the unemployment status in the neighbourhood and of unemployed peers' behaviours. These effects are particularly important for search through networks. If having unemployed neighbours tends to lower the social pressure of remaining unemployed and to hinder job search, a higher proportion of unemployed peers using actively professional, personal networks or social media for finding a job increases the individual's probability to use the same channel. These imitative effects could occur through social pressure with the need to conform to the job search behaviours promoted within the neighbourhood or through a word-of-mouth learning process through which unemployed neighbours would give each other tips and advice, thus reducing the costs related to job search. We also find some contextual neighbourhood effects for total search intensity and search through networks. Namely, a higher share of high-level occupations in a neighbourhood fosters total search intensity and more specifically search through networks, which suggests that interactions with neighbours are important in creating networks and in access to information on job opportunities.

The remainder of the paper is organised as follows. Section 2 places this paper in the context of the literature on job search behaviours and of the broader literature on neighbourhood effects applied to labour market outcomes and presents the key points involved in the identification of neighbourhood effects. Section 3 describes the French Labour Force Survey and presents some descriptive statistics. Section 4 outlines the empirical design and the methods used to tackle 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

2.1 Determinants of job search behaviours

The literature regarding the importance of job search in return to employment underlines that some job search channels are more effective than others, that they involve different costs, are more or less accessible, and that therefore anticipation about these efficiencies and costs might influence job search effort. In their typology of job search channels, Piercy and Lee (2019) show using US data that older and less-privileged individuals tend to use more formal job search channels (printed advertisements, career events, and employment agencies) which are more time-consuming, while highly educated and internet-friendly individuals favour the use of informal channels (professional, personal contacts or social media) which seem to be today the major source of information about jobs. Personal, professional relations and networks are indeed suggested as the most efficient ways of finding a job, even if not accessible to all. Granovetter (1995) for instance concludes that jobs are often found through contacts formed long before seeking employment and that almost 57% of individuals found out about their current job through personal contacts while 19% used more formal means (public and private agencies, placement services, professional associations). Montgomery (1991) also underlines that the use of networks may help potential employers to overcome a problem of asymmetric information and produce better matches, while Caliendo et al. (2011) show using German data that unemployed individuals using large informal social networks have a higher search productivity leading to better paid jobs. The importance of job search in the return to employment thus depends on the channels that can be mobilised while the anticipation effects with regards to the efficiency of a particular channel can influence job search intensity.

From the urban search models perspective, Patacchini and Zenou (2005) study the impact of different time commuting costs on search intensity. Using a panel of sub-regional data from the English Labour Force Survey, they show that higher time commutes reduce search intensity as unemployed individuals residing further away from jobs or using more time-consuming transportation modes not only have a higher cost today of gathering information on job opportunities but also a higher commuting cost tomorrow if they find a job. In another paper, Patacchini and Zenou (2006) show, using the same data, that the average search intensity of unemployed individuals, measured at the aggregate level by the ratio of active non-employed job seekers to the potential unemployed job seekers in each area, is positively related to the labour market tightness, defined as the ratio between vacancies and unemployed, and to higher costs of living. According to their theoretical model, an increase in the labour market tightness leads to more efforts in search activities as the prospects of leaving unemployment increase.[2] On the other hand, a higher cost of living increases the expected lifetime differences between employment and unemployment making the employment status more desirable because wages are most of the time adjusted to cost of living whereas unemployment benefits are not.

With these exceptions, we can say that there is a scarce literature on the determinants of job search behaviours, which contrasts with the important role of job search in theoretical labour economic models.

2.2 Neighbourhood effects and labour-market related outcomes

The neighbourhood effects literature gives some insight into how the job search channels and search intensities of unemployed individuals can be impacted by neighbours' characteristics and behaviours (Durlauf, 2004).

Wilson (1987) is one of the first to argue that interactions with neighbours are important in understanding the persistence of inner city poverty and are likely to affect human capital acquisition process, attitudes towards work or access to information on job opportunities. More recently, several studies have underlined how living in neighbourhoods of low socioeconomic status affects unemployment probability (Andersson, 2004; Dujardin et al., 2008; Bauer et al., 2011; Alivon and Guillain, 2018; Eilers et al., 2021). With a similar rationale, other studies have focused on the role played by networks in finding employment. Bayer et al. (2008) underline the importance of interactions with employed neighbours in access to information on job opportunities and in creation of networks. Using Census data on residential and employment locations

[2] In their model, unemployed individuals decide upon their search intensity based on a trade-off between short-run losses due to higher costs of search effort (more phone calls, more interviews, more commuting, less leisure, less composite consumption) and long run gains with higher chances to find a job.

in the Boston metropolitan area, they define neighbourhood at a very narrow level (block), and examine if individuals residing in the same block are more likely to work together than those of nearby blocks. Their main result is that residing in the same versus nearby blocks increases the probability of working together by 33% therefore revealing the presence of neighbourhood effects in finding job opportunities. This result is similar to Topa (2001)'s previous study in Chicago in 1990 where he finds that a one standard deviation increase in the employment rate of neighbouring tracts increases employment by 1.3% in a Census tract due to exchange in information about job openings. It is also in line with Jahn and Neugart (2020) who analyse, using detailed spatial data from Germany, which channels are at work regarding the influence of the employment status of neighbours on the employment probability of a newly displaced worker, and find that a 10% point increase in the neighbourhood employment rate increases the probability of re-employment after six months by 0.9% due to the transmission of information on job opportunities.

Other recent studies also emphasize the importance of residential local networks (see e.g. the survey by Topa and Zenou, 2015). Using US cross-sectional data that allows to capture employer-employee matches and to identify very precisely place of residence (at the census tract level) and place of work (at the establishment level), Hellerstein et al. (2011) find evidence of the importance of connections between neighbours in the assignment of workers into firms.[3] Their measure for the importance of local market networks is computed by the extent of network isolation (i.e. the fraction of co-workers who are residential neighbours) that occurs due to randomness, compared to actual data, and captures the disproportionate presence of co-residents in a worker's own firm. In another paper, Hellerstein et al. (2014) study the productivity of these residential local networks and find that they have significant effects in reducing turnover and increasing earnings. This indeed implies that networks within neighbourhoods favour good and efficient matches on the labour market. With a similar identification strategy than in Bayer et al. (2008) and using detailed US employer-employee data, Schmutte (2015) analyses the impact of the quality of local social network within small neighbourhoods (census block groups) on earnings and place of work.[4] He underlines the presence of local spillovers and shows that local referrals not only favour high-ability workers-firm matches but that being surrounded by neighbours with high-quality jobs, earning high wages, favours employment in high-paying firms as they can provide direct referrals to employers, share information about job opportunities, about pay differentials across firms in the area or on how to find a good job around the neighbourhood. Finally, Cingano and Rosolia (2012) find, using data covering the period 1974-1997 in Northern Italy, that the employment status of professional relations has an important effect on re-employment, especially if these contacts have recently looked for a job, if they are spatially close and if they share strong ties and similar skills with the unemployed individual.

These phenomenon could also be important in France, as shown by the recent survey *"Mon quartier, mes voisins"*, which underlines that neighbourhood relationships remain at high levels in France, that they are more frequent at the level of the building than the neighbourhood, and that they can play a role in job search via exchanges of information on job opportunities (Bonneval, 2021; Authier and Cayouette-Remblière, 2021).[5]

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[3] They use the 2000 Decennial Employer-Employee Database (DEED).

[4] He uses data from the Longitudinal Employer-Household Dynamics (LEHD) program of the US Census Bureau.

[5] This survey "My neighbourhood, my neighbours" was conducted by sociologists from the Ined (National Institute of Demographic Studies) and the Max Weber Centre.

2.3 Identification of neighbourhood effects

The mechanisms at play behind these neighbourhood effects however remain often a black box, which is why it is important to reframe this literature within the larger stream of research on social interactions. Manski (1993) developed a simple model of social interactions that can be easily adapted to neighbourhood effects. In his widely cited article, he distinguishes three mechanisms that can explain why individuals belonging to a same group tend to behave similarly: (i) *endogenous effects* represent the impact of the average behaviour of a group on individual behaviour; (ii) *contextual effects* translate how the average characteristics of the group influence individual behaviour and (iii) *correlated effects* arise because individuals in the same group tend to behave similarly as they share similar individual characteristics and are exposed to non-random group selection or because they share similar institutional environments and are therefore exposed to common, part of which unobserved, factors. The main consequence of the existence of endogenous effects is a social multiplier effect, which represents the fact that each individual behaviour is amplified at the aggregate level by its influence on others' behaviour.

Different mechanisms can explain the existence of *endogenous peer effects* in job search behaviours of unemployed individuals. First, psychological factors and social pressure, with the need to conform to the social norms promoted within the reference group, can be a first channel through which these imitative behaviours occur. If an unemployed individual lives in a neighbourhood where being unemployed is frowned upon, and where his unemployed neighbours are actively looking for work, he might face a cost of deviating from the group's social norm and receive social pressure to act similarly. Second, the conformity in behaviours can also occur through a word of mouth learning process. The more individuals of a group exert a certain behaviour, the more the costs associated to this behaviour are reduced for other members of the group. We can for instance imagine that unemployed neighbours who face the same situation would help each other through advice and tips regarding what they consider as the most efficient job search methods which will therefore be associated to higher utility levels. This seems all the more 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 and therefore the prospects of re-employment. Liu, Patacchini, and Zenou (2014) use the terms "*local average effect*" and "*local aggregate effect*" to distinguish these two kinds of mechanisms. Nicodemo and García (2015) show in the case of Colombia that the use of networks vs. non-networks job search methods is influenced by neighbours' choices and the way they find employment. A higher proportion of neighbours using social networks for finding a job increases the probability to use the same channel.

Regarding *contextual effects*, the aforementioned literature on the importance of the socio-economic environment of a neighbourhood and more particularly of networks within neighbourhoods on employment probability can give us some insight on the neighbours' characteristics that may foster job search. We can therefore suppose that a higher rate of employed individuals in a neighbourhood would offer better access to information on job opportunities and to a network that facilitates job search, especially if these employed individuals are in high-level occupations, while the more individuals are surrounded by highly-educated neighbours, the more they are immersed in a cultural environment that is more conducive to job search.

Two identification issues are however at the heart of the long-running debate about the existence and amplitude of neighbourhood effects (Durlauf, 2004). The first identification problem is the *group endogeneity issue* that produces correlated effects in Manski's terminology. Adapted to the neighbourhood effects context, it underscores a problem related to the non-random sorting of individuals into neighbourhoods. While choosing a place of residence, individuals firstly face the classic sorting resulting from the working of the housing market, with a price effect that implies that individuals who share similar characteristics (income, level of education, etc.) tend to locate in the same place. Individuals most at risk of unemployment are thus often located in the same neighbourhoods. On top of that, individuals may choose a place based on anticipated social interactions effects. Parents may for instance choose to live in a neighbourhood based on expected peer effects at school and therefore locate near individuals with whom they share socio-cultural similarities with. There is thus, a very likely *location endogeneity issue*. Another source of correlated effects is the existence of random shocks common to all individuals in a neighbourhood. If not controlled for, these correlated effects create a bias in the estimates of social interaction effects (Durlauf, 2004).

Different strategies have been developed to deal with correlated effects in social interaction models. A fruitful approach in the case of neighbourhood effects has been proposed by Bayer et al. (2008), who provide an identification strategy to overcome the issue of spatial sorting. Using Census data in the Boston metropolitan area, they define two nested levels of neighbourhood: the Census tract and the different blocks within this Census tract. Workers can choose a Census tract (block group) to live in but not a specific block within this Census tract (block group) as this depends on the housing available at the time of mobility. Block-level location can therefore be considered as exogenous once controlled for a higher level of location with the introduction of block group (Census tract) fixed-effects. This strategy has since then been applied in other contexts (Schmutte, 2015; Hawranek and Schanne, 2014; Solignac and Tô, 2018; Grinblatt et al., 2008) and more specifically, in line with this work, using the French Labour Force Survey by Hémet and Malgouyres (2018) to identify the effect of neighbourhood diversity on employment prospects, by Chareyron, Domingues, and Lieno-Gaillardon (2021) to highlight the role played by neighbours on welfare participation and by Chareyron, Chung, and Domingues (2021) to stress the impact of local ethnic diversity on educational outcomes.

The second issue, called the *reflection issue*, concerns the econometric identification of endogenous effects *versus* contextual effects. It occurs in the most common model, namely the linear-in-means model. As stated by Liu et al. (2014), *"the reflection problem arises because, in a linear-in-means model, individuals are affected by all individuals belonging to their group and by nobody outside the group, and thus the simultaneity in behaviour of individuals in the same group introduces a perfect collinearity between the endogenous effect and the contextual effect"*. This happens because the endogenous effect is the mean outcome of the group and the individual behaviour is assumed to react linearly its determinants, namely endogenous, contextual, and own effects.

The former two conditions that forbid to disentangle endogenous from contextual effects suggest two main ways for solving this issue. First, the literature has early considered the identification conditions provided by non-linear models. The use of non-linear estimation techniques to overcome the reflection problem was already mentioned in Manski (1993). A formal characterization of the conditions for identification was provided, first for binary outcomes and then for multinomial outcomes by Brock and Durlauf (2001, 2002, 2007). The intuition is that, unlike linear-in-means models, this type of models introduces a non-linear relationship between the individual behaviour and the determinants of this behaviour which results in the absence of perfect collinearity between the group average characteristics and the mean outcome and contributes to enabling the identification of their effects. Considering other non-linear models is still in progress, but a recent paper provides a formal analysis of identification in count models (Houndetoungan, 2022).

Second, the growing literature in the economics of networks uses the potential intransitivity of relations within networks as a mean to identifiy endogenous and contextual effects. These studies show that the reflection issue can be solved *"when peers of peers are not peers"* and the reference groups are not a partition of the population, so that the reference group is specific to each individual (Bramoullé, Djebbari, and Fortin, 2020). The key point in such a setting is that *"the characteristics of peers of peers who are not peers affect an individual's outcome only through their effect on peers' outcomes."*, which allows peers of peers characteristics to be used as instruments for the peers' behaviour (Bramoullé et al., 2020). Such an identification strategy is possible if each individual can be associated with a unique reference group, network, neighbourhood, which requires very precise data. Empirical contributions based on this strategy include for instance Grinblatt et al. (2008) and Giorgi and Pellizzari (2014).

A less obvious identification strategy was first explored by Lee (2007) and then more thoroughly investigated by Davezies, D'Haultfoeuille, and Fougère (2009) and Boucher, Bramoullé, Djebbari, and Fortin (2014). It consists in excluding the individual when computing the group averages for her endogenous and contextual effects. Exclusive averaging allows identification in the linear-in-means model provided that there is enough variance in group size and the group size is not too large.

Another strategy is the use of a dynamic linear-in-means model with the introduction of lagged social interactions independent variables, which supposes that endogenous and contextual effects are not contemporaneous. Such strategy has been used for example in Towe and Lawley (2013) who are interested in the neighbourhood effects of forclosures. To exploit such structure, one however needs to provide a justification to the lag in the transmission of these effects.

Overall, the neighbourhood effects literature applied to labour market outcomes gives us some insight into how interactions with neighbours could affect job search behaviours and how they could reinforce spatial inequalities in terms of urban unemployment. These mechanisms have not yet been directly applied to job search behaviours. There has also been very few papers targeting job search behaviours in an empirical analysis of urban unemployment inequalities, to the exception of Patacchini and Zenou (2005, 2006) who provide search intensity variables that are measured at the aggregate sub-regional level as the ratio between active job-seekers and potential active job seekers. We aim to fill these gaps and contribute to the existing literature by providing, through a contextual and endogenous effects model à la Manski (1993) applied to French data, a detailed analysis of the neighbourhood effects involved in job search behaviours. Our results might participate in the debate regarding the question of inequalities between residents of privileged and deprived neighbourhoods.

3 Data and descriptive statistics

3.1 The French Labour Force Survey

This paper relies on data from the French Labour Force Survey (*Enquête Emploi*) of the French National Institute for Statistics and Economic Studies (*Institut national de la statistique et des études économiques*, INSEE) over the period 2014 to 2019.

The French Labour Force Survey (FLFS in the following) is since 1950 a unique source for understanding the state and the evolution of the labour market in France. It provides a detailed description of households, with the characteristics of the main job held, the level of and access to education, the geographical and social origin, the health status and labour market trajectories of their members above 15. The FLFS definition of activity status is in line with the ILO: it refers to a respondent's activity status during a specific period, in the case 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 sample is a panel of dwellings surveyed for a period of six consecutive quarters, which can also be considered as a panel of individuals.[6,7] Over one quarter, the FLFS sample comprises about 67,000 dwellings and 108,000 surveyed individuals. The FLFS has a specific sampling design that makes it very useful to study neighbourhood effects and that will be central to their identification in our work.[8] The FLFS can be described as areal and rotating:

- *An areal sampling design* - The FLFS baseline sample is constituted of 2,500 sectors of approximately 120 dwellings.[9] Each sector is split into six contiguous or very close clusters that contain each about 20 contiguous dwellings and that correspond in our analysis to local neighbourhoods.
- *A panel rotating survey* - Each cluster of a sector is randomly given an order of inclusion into the sample going from 1 to 6. The first cluster of a sector is surveyed for a period of six quarters, before being replaced by the second one over the next six quarters. This procedure is carried on until all six clusters of the sector are surveyed, and the sector is replaced by a new one.

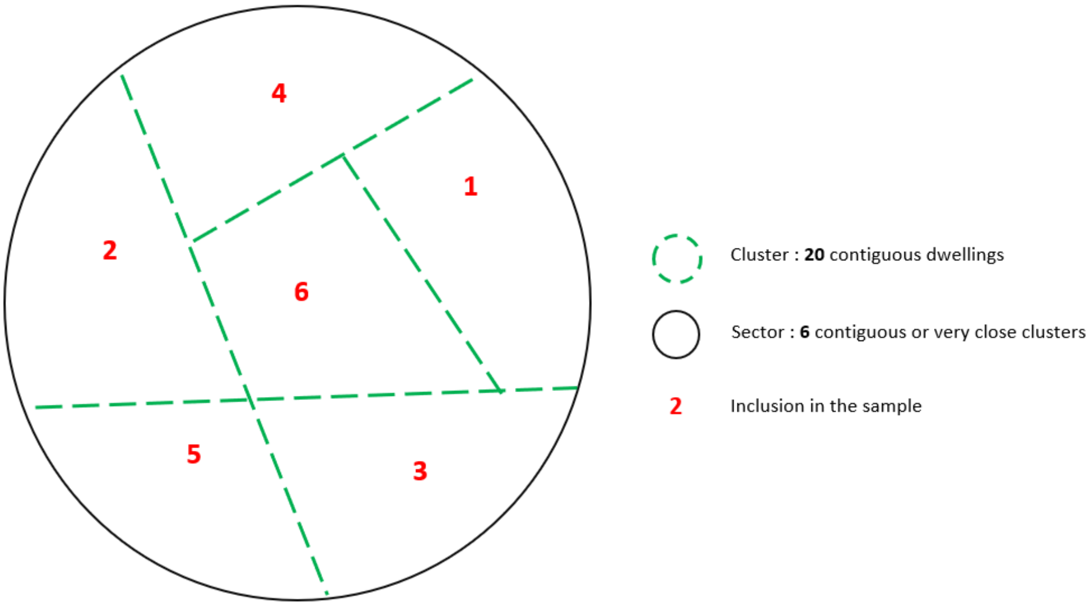

Figure 1: Sampling design of the FLFS

Figure 1 above gives some insight into how the FLFS sampling scheme works. The first cluster of this sector is surveyed for instance from the 1st quarter of 2014 to the 2nd quarter of 2015,

[6]As it is a panel of dwellings, individuals who leave the housing unit for various reasons (split couples, moving out, young adults leaving their parents' house etc.) are not followed up in the survey.

[7]Some dwellings and individuals part of these dwellings do not appear over six consecutive quarters due to split housing, non-responding or out-of-scope dwelling in a given quarter, incomplete individual questionnaire, household not re-interviewed in the intermediate wave because it consists only of inactive people aged 65 or over.

[8]These particular features of the survey have been used in Hémet and Malgouyres (2018) to identify the effect of neighbourhood diversity on employment prospects, in Chareyron, Domingues, and Lieno-Gaillardon (2021) to highlight the role played by neighbours on welfare participation and in Chareyron, Chung, and Domingues (2021) to stress the impact of local ethnic diversity on educational outcomes.

[9]Only dwellings considered as main residences are included in the sample.

before being replaced in the sample by the second cluster of the same sector which will in turn be surveyed over a period of six consecutive quarters (from the third quarter of 2015 to the fourth quarter of 2016).

These features explain why the FLFS is well suited for this research paper. The survey provides, with the presence of clusters of 20 contiguous dwellings, a precise and accurate definition of a local neighbourhood. These clusters, which are all surveyed for a period of six consecutive quarters, are by definition of very small geographical size. In order to understand to what extent these clusters correspond to a very precise neighbourhood level, it seems important to us here to recall their construction rules, in particular in urban areas, on which we will focus in this paper. In urban areas, a cluster (local neighbourhood) very often corresponds to the different dwellings of an entire building or to a part i.e. specific floors of that building, having in mind that the INSEE cluster construction rule requires that all dwellings part of the same floor be included in the same cluster. Figure 4 in the Appendix gives us the example of a cluster of 28 dwellings, all in the same building in Paris. Figure 5 of the Appendix presents the example of a cluster of 23 dwellings in a rural community. Even in this case of a low urbanized area, all the dwellings of the same cluster are located at the intersection of two streets and constitute therefore a very small neighbourhood level. Overall, residents of dwellings part of the same cluster can therefore be considered as close neighbours who can interact on a daily basis.

This survey also provides, with clusters aggregated into sectors, two nested levels of neighbourhoods. This means that we can observe individuals living in very close or contiguous clusters (local neighbourhoods) within the same sector, which is, as will be explained in Section 4, a key to the identification of neighbourhood effects in our analysis. Clusters part of the same sector might in the case of urban areas be very close. As mentioned by the service in charge of the FLFS production: "*By the very 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*". Note however that individuals part of contiguous clusters in a sector are not surveyed at the same time.

The empirical analysis in this paper covers the period going from the first quarter of the year 2014 to the fourth quarter of the year 2019: a total of twenty-four quarters within which we can observe a maximum of four clusters in the same sector.

To analyse job search behaviours, we select individuals aged 15 or more, in accordance with the ILO definition of persons of working age, and because we are interested in behaviours in urban areas, we focus on large urban areas in mainland France.[10] Moreover, as we observe only 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 to unemployed invidividuals. Finally, for reasons that will be clarified in Section 4, we keep only one unemployment period (the most recent one) for each unemployed individual. This leaves us with an estimation sample that comprises 29,345 individuals, each observed once, 2,645 sectors and 7,899 clusters (local neighbourhoods).

3.2 The job search variables

We measure search intensity as the number of times an individual answered "yes" to a question asking whether she took an action for searching a job through a specific channel. There are

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

twenty-one such questions in the FLFS which we group to define five job search channels variables and total search intensity.

The first job search variable refers to the search intensity related to *contact with employment organisations* such as the French National Employment Agency (*Pôle Emploi*), the Agency for the employment of Managers in France (*Association Pour l'Emploi des Cadres*, APEC), a placement operator, a temporary employment (interim) agency, the chamber of commerce and industry, or any other public institute.[11] This variable refers to the most official job search methods. The second job variable refers to *more active and direct actions leading to re-employment.* This type of actions is already a first step towards employment: interviews, entry tests for the civil service or private companies, unsolicited (speculative) applications, responding to a job offer, participation in trade fairs or job forums. The *job search through networks* variable refers to both the use of personal (family, friends) and professional connections to find a job, but also to the use of social media.[12,13] The fourth job search variable refers to the job search *leading to entrepreneurship* and actions such as soughing to takeover a business, an established practice or private offices. It also corresponds to the search for land, premises or equipment, the search for financial resources or the application for a permit, licence or authorisation to set up a business. We also have a job search variable that refers to *the passive search for a job*, i.e. waiting for the results of previous procedures (interviews, entry tests, etc.) or a call from *Pôle Emploi* (the French National Employment Agency), a placement operator or any association for professional insertion. Finally, the total job search intensity variable sums together all the search intensity variables previously mentioned, is a measure for search intensity in general and therefore constitutes a first basis for this analysis.

Figure 6 in the Appendix details the FLFS survey questions used for the computation of each of the job search variables while Figure 7 gives an example regarding how responses to these questions subsequently define the different job search intensities. If an individual answers "yes" to one question regarding search through organisations, then his search through organisations intensity equals to 1. If he answers "yes" to three questions regarding active and direct search, then his active and direct search intensity equals to 3. If he answered "yes" to two questions related to search through networks, then his search through networks intensity equals to 2. With zero "yes" responses to passive search and search leading to entrepreneurship related questions, his total search intensity consequently sums up to 6. As they are positive and discrete, these dependent variables can therefore be considered as *count data.* Given the number of related questions, the search through networks and search leading to entrepreneurship variables can vary up to a maximum of 4, the search through active and direct actions up to maximum of 7, the search through official employment organisations and the passive job search variable up to a maximum of 3 and the total job search intensity up to a maximum of 21. However, since very few individuals in our sample of analysis use the job search channels related to the entrepreneurship and passive search, we will focus on job search through employment organisations, through active and direct actions, through networks, and on total search intensity.[14]

[11] In terms of contact with the French National Employment Agency (*Pôle Emploi*), only the personal steps taken in the context of job search or training are included in this variable. It does not include contacts related to mandatory follow-up interviews or contacts to solve a problem concerning the payment of unemployment benefits.

[12] Even if we are interested in our analysis in underlining the existence of neighbourhood effects in the job search behaviours of unemployed individuals, the job search through networks variable is not limited to neighbours. We hypothesize that unemployed individuals imitate the job search behaviours of their neighbours but this does not mean that they only use networks within the neighbourhood.

[13] With the data we have, we cannot know 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 these three types of networks to find a job and have no information on the intensity of the use of any of these three types of networks.

[14] With total search intensity that still comprises job search leading to entrepreneurship and passive job search.

Table 1 below describes the distribution of these four job search variables in the estimation sample. The total search intensity variable is rather well distributed: 9% of individuals do not search at all, 19% have a total search intensity that is either 1 or 2, 31% take 3 or 4 actions towards job search while 41% have a total search intensity that is equal or superior to 5.[15] Approximately one third of unemployed individuals in the sample do not search through networks, 51% have a search through networks intensity that is 1 or 2 while very few individuals have a search through networks intensity that is above 2. A majority (74%) of individuals carry between 1 and 3 direct and active actions towards employment, 15.7% do not use this type of job search channel while very few carry more than 3 direct and active actions towards employment. Finally, nearly half of the sampled individuals do not use job search through employment organisations while another half contact 1 or 2 organisations.

Table 1: Distribution (in %) of the job search variables in the estimation sample

Search intensity	0	1	2	3	4	5	6	7	8	9	10	11:15
Total	8.9	7.2	11.9	15.6	15.8	14.4	11.2	7.8	4.4	2.0	0.6	0.1
Networks	31.7	27.8	23.8	12.6	4.0							
Active and direct	15.7	24.3	24.5	24.9	10.1	0.4	0.007					
Organisations	46.7	35.6	16.0	1.7								
Observations						29,345						

Source: French Labour Force Survey, estimation sample as defined in the text.
Note: 15.8 % of unemployed individuals in the sample have a total search intensity of 4. 11:15 corresponds to search intensities that are either 11, 12, 13, 14 or 15.

3.3 Descriptive statistics: characteristics of unemployed individuals

Table 2 presents some descriptive statistics for the characteristics of the unemployed individuals present in the estimation sample. This sample is representative of the French labour market and therefore mirrors unemployed individuals in urban areas in France.

Table 2: Descriptive statistics (in %) - Estimation sample

	All
QP [a]	16.4
Housing tenure [b]	
Homebuyers	16.4
Homeowners	22.2
Public tenants	28.2
Private tenants	29.5
Furnished units	1.4
Free accommodation	2.1
Usufructuary	0.1
Female	49.2
Child	38.4
Age	
Age 15+	39.1
Age 30+	21.6
Age 40+	18.8
Age 50+	16.3
Age 60+	4.4
Nationality	

[15]It might surprising at first sight that some individuals considered as unemployed according to our definition that follows the precepts of the ILO do not search at all. The reason for this observation is that our definition of search excludes contacts with *Pôle Emploi* (the French National Employment Agency) if they are not really devoted to searching for a job.

French	88
Foreigner	12
Education/Diploma [c]	
Bachelor, Master, PhD	11.6
Bac+3 schools	3.1
Associate degree	0.8
Higher National Diploma	8.7
Paramedical/Social (Bac +2)	0.9
General Baccalaureate	7.3
Technical/Professional Baccalaureate	15.5
Vocational diploma	24.4
Middle School Cerificate	7.2
Primary School Certificate	1.4
No diploma	18.3
NAs	0.9
Previous occupation [c]	
Farmers	0.1
Independent workers	2.9
High-level occupations	6.9
Intermediate occupations	14.1
Low level white-collars	28.8
Blue-collar workers	28.9
Unemployed (have never worked)	17.2
Others (N.A)	1
Urban unit size	
Rural community	14.4
Less than 20,000 inhabitants	11
20,000 to 200,000 inhabitants	23.6
More than 200,000 inhabitants (except Paris)	33.9
Paris urban area	17
Observations	29,345

[a] QP (*Quartiers Prioritaires*) refers to unemployed individuals living in Priority Zones (deprived neighbourhoods).
[b] Housing tenure: Public housing tenants refer to the French "*locataires de logements HLM*"; private tenants refer to private housing tenants of dwellings rented empty; furnished units refer to private housing tenants of furnished dwellings or hotel rooms; free accommodation can either be at parents' or friends' place or provided by the employer.
[c] For a definition of diplomas and previous occupations, see Table 3.

There is a very high proportion of young unemployed individuals in the sample: 39% of them are aged between 15 and 29. This young share of unemployed individuals has indeed increased in recent years in France and suffer from a degraded economic situation (Céreq, 2012). Unemployed individuals are generally low-skilled. Approximately 40% of sampled individuals hold "low-level" short-term professional diplomas (vocational diploma or professional baccalaureate), while the majority of them were either blue-collar workers (28.9%) or low-level white collars (28.8%) before losing their job. Individuals present in our sample have low income levels and 28% of them are public tenants. Only 39% of them are homebuyers/homeowners, to be compared with 58% in the general population over the period 2014 to 2019.[16] 16.4% of individuals live in deprived neighbourhoods i.e. French Priority Zones (QP, *Quartiers Prioritaires*). This is not surprising as these QP identify urban areas with a high concentration of low-income population.[17]

[16] *Source:* INSEE and standard deviationES (Data and Statistical Studies Department, *Source: Service de la Donnée et des études Statistiques*), annual estimates of the housing stock.

[17] The QP are since 2014 the main target of the French urban policies and are under the supervision of the French Observatory of Urban Policies (ONPV, *Observatoire National des Politiques de la Ville*). They are defined on the basis of a single quantitative criterion, that of income, by precisely identifying via a grid method the areas of urban concentration of low-income population. Low income is defined relatively to both the average income

4 Empirical strategy

In this paper, we use a model à la Manski (1993) to study the local-neighbourhood-related contextual and endogenous effects involved in the search process on the labour market. We want to identify the impact on unemployed individuals' job search behaviours, namely intensity and channels used, of (i) other unemployed neighbours' job search behaviours, that is the endogenous effects, and (ii) neighbours' characteristics, that is the contextual effects. The endogenous contextual and endogenous effects are defined at the cluster level, the finest level of neighbourhood, where daily interactions between neighbours are likely to take place.[18]

The *endogenous effects* in our analysis are intended to capture how the job search behaviours (channels used and intensity) of unemployed individuals are influenced by that of their unemployed neighbours. The aim is to underline the existence of peer effects in the job search behaviours of unemployed individuals within a neighbourhood. Different mechanisms can explain the existence of peer effects. A first channel would be through an imitation effect, with a need for conformity to the behaviours and social norms promoted within the reference group. If an unemployed individual lives in a neighbourhood where being unemployed is frowned upon, and where his unemployed neighbours are actively looking for work, he might face social pressure to act similarly. Another channel through which these peer effects can operate is through the spread of information. The job search of unemployed neighbours can make the job search of an unemployed individual less costly or more efficient. We can imagine here mutual help, advice, tips, between neighbours who face the same situation that lead to an increase in job search effort. Liu et al. (2014) use the terms "*local average effect*" (social pressure) and "*local aggregate effect*" (cost of search effort) to distinguish these two channels.

The *contextual effects* in our analysis aim to identify the average neighbours' characteristics that favour job search effort. The literature on neighbourhood effects has underlined the existence of social interaction effects on unemployment duration and on return to employment. We wish here to apply the insight from this type of literature to job search behaviours. Drawing on the neighbourhood effects literature, we hypothesize that a lower local employment rate (or a higher local unemployment rate) may push to a lower job search intensity as unemployed individuals may have negative rational expectations about their chances of finding a job (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 hypothesize that a higher rate of employed individuals in a neighbourhood not only gives incentives because of social stigma to find a job more quickly but also offers 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 through a better quality of information and the possibility of direct referrals to employers facilitate worker-firm matches (Schmutte, 2015). We can easily imagine a meeting in the neighbourhood between an employed and an unemployed neighbour. A few words would be enough to make the unemployed person's situation known or maybe the employed neighbour has heard about it by word of mouth. The latter could then share the job offers he or she knows about or offer other solutions, such as proposing to contact his or her acquaintances to find a job.

of the urban area in which the QP is located and to the average income in mainland France. The source for measuring household income is the INSEE survey "*Enquête revenus fiscaux et sociaux*" (ERFS).

[18] In addition to the determinants of job search behaviour which we consider here, there are other factors related to social interactions occurring within other groups, such as those related to friendship or family relationships. We focus here on local neighbourhoods related social interactions.

Another stem of the neighbourhood effects literature shows that the higher the level of education in a neighbourhood, 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). Unemployed individuals indeed meet in the neighbourhood highly educated individuals or individuals working in high-level occupations, whom they may consider as role models and who can give them various keys related to job search.

The contextual effects we consider here reflect these three types of mechanisms and consist in the shares of neighbours who are employed, who are highly educated and who are in high-level occupations. All employed, unemployed and inactive individuals present in a cluster at a specific quarter are included in the computation of the share of employed and university graduates neighbours. Indeed, we want these variables to reflect the real probability of running either into someone in employment in the neighbourhood and therefore in connection with the labour market or into someone with a university degree that might give various keys with regards to job search. The share of high-level occupations neighbours is computed only among employed individuals present in a cluster at a specific quarter. We want this last variable to reflect the probability to be in touch with individuals who are connected to the labour market, are in positions that may provide access to higher-quality information and who could more potentially influence a future labour market match.

In the following, we first present the empirical model and then develop in more details how this empirical model deals with the location endogeneity and reflection issues.

4.1 The empirical model

Due to the nature of the dependent variables, the following fixed-effects Poisson model (Wooldridge, 1999) is estimated.[19] It can be writen as follows:

$$E(Y_{igst}|\mathbb{X}) = \exp\left(\alpha \mathbb{1}_{n_{igst}>0} + \beta \mathbb{1}_{n_{igst}>0} \times E(Y_t|g\backslash_i) + \sum_{k=1}^{K} \gamma_k E(Z_{kt}|g\backslash_i) + \sum_{l=1}^{L} \delta_l X_{ligs} + \eta_s + \theta_t\right) \quad (1)$$

Where:

- Y_{igst} refers to one of the three job search channels intensity (search through networks, search through official employment organisations or search through active and direct actions) or to the total search intensity of individual i part of cluster g and sector s at quarter t,
- n_{igst} is the number of unemployed neighbours of individual i at quarter t
- $\mathbb{1}_{n_{igst}>0}$ designates observations for which unemployed neighbours are present in the same quarter and α may account for the perception of the unemployment status in the neighbourhood,
- $E(Y_t|g\backslash_i) = \sum_{j=1}^{n_{igst}} Y_{jgst}/n_{igst}$ corresponds to the average search intensity linked to one of the three same job search channels (search through networks, search through official employment organisations or search through active and direct actions) or to the average total search of i's unemployed neighbours in cluster g at quarter t; β tests for endogenous effects in Manski's terminology,

[19]The Poisson fixed-effects model is characterized by strong consistency properties as shown by Wooldridge (1999). It is a model that is fully robust to distributional misspecification and whose coefficients can be interpreted as partial elasticities.

- $E(Z_{kt}|g\backslash_i)$ $(k = 1, ..., K)$ refers to a set of K average characteristics of i's neighbours in cluster g at quarter t that favour job search effort. γ_k tests for contextual effects in Manski's terminology. We distinguish three contextual effects variables: (i) the share of employed neighbours ; (ii) the share of university degree graduates neighbours (i.e. a post-baccalaureate diploma); (iii) the share of high-level occupations neighbours (i.e. senior executives and higher intellectual occupations, *cadres et professions intellectuelles supérieures*) among employed neighbours, in cluster g at quarter t,
- X_{ligs} $(l = 1, ..., L)$ are L individual characteristics to control for fixed observed heterogeneity. These characteristics may affect the different dimensions of job search and include: age, sex, diploma, previous occupation, nationality and having or not a child,
- θ_t controls for quarterly time effects,[20]
- η_s is a sector fixed-effect that captures all observed and unobserved characteristics common to all individuals living in the same sector that impact search intensity and help us to deal with the location endogeneity issue,
- $\mathbb{X} = \mathbb{1}_{n_{igst}>0}, E(Y_t|g\backslash_i), E(Z_{kt}|g\backslash_i), X_{ligs}, \eta_s, \theta_t$.

As Bertrand, Duflo, and Mullainathan (2004) show that in practice the idiosyncratic errors of a fixed-effects estimation are often correlated within groups understating the usual standard errors of the estimators, sector-robust standard errors are used in the regressions. They take into account the fact that individuals located in the same sector are subject to the same shocks. The model is estimated by conditional quasi-maximum likelihood.

As we do not want to create unnecessary duplicates, this model is estimated on the sample defined in Section 3, which comprises only one unemployment spell (the most recent one) for each unemployed individual.[21]

Table 3 presents the definition of all explanatory variables in equation 1 and some variants used in the robustness checks.

4.2 A method à la Bayer, Ross & Topa (2008) to deal with the location endogeneity issue

One of the two identification problems at the heart of the long-running debate when testing for the existence and the nature of neighbourhood effects is the *location endogeneity issue*. It is due to the non-random sorting of individuals into neighbourhoods and corresponds to the *correlated effects* in Manski's terminology.

The inclusion of sector fixed-effects in our estimation, with two nested levels of neighbourhoods and a control for the upper level, helps us to deal with this location endogeneity issue in a way similar to Bayer et al. (2008). The hypothesis is that even if households select a neighbourhood where they want to locate, here the sector, they cannot select a specific location within this

[20] It is one of the quarter dummies covering the period of analysis i.e. Q12014 to Q42019, except one, Q12016 which contains the maximum of observations and is the reference.

[21] We could have, with the inclusion of individual fixed-effects, used the time dimension of the FLFS and identify endogenous and contextual effects on the basis of their variability across the different unemployment periods of each individual. However, the majority of unemployed individuals in our sample face only one period of unemployment, which leaves us with not enough variability to identify these effects. Even if there were many individuals who were unemployed over the six quarters of observation, one could be sceptical about the variability and therefore identification of these effects, especially contextual effects, within only six quarters.

neighbourhood i.e the cluster. This is especially true in our case as the FLFS offers a very narrow definition of neighbourhoods. Moreover, sectors and clusters *"do not correspond to any administrative or official frontiers. People do not know where the borders are, and more generally do not even know what a cluster or a sector is, as it is only used as the sampling unit of the FLFS"* (Hémet and Malgouyres, 2018).

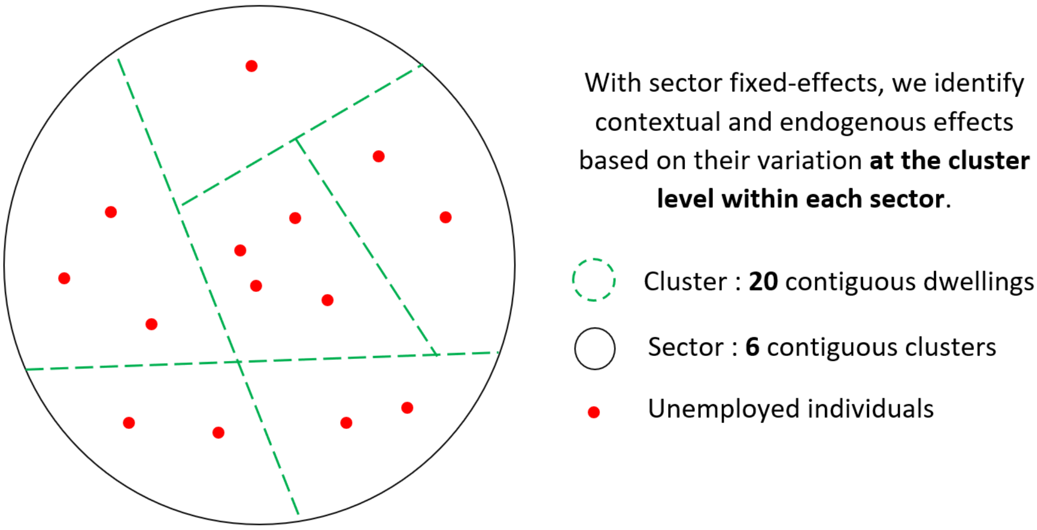

Figure 2: Dealing with the location endogeneity issue with sector fixed-effects

As shown in Figure 2, we identify social interaction effects (as opposed to correlated effects) based on their variation at the cluster level within each sector. Our identification strategy relies on assuming that, once controlled for a higher level of location with the inclusion of sector fixed-effects, location within clusters can be considered as exogenous. As a consequence, there is no correlation in the unobservables affecting an individual's job search behaviour and the ones affecting her neighbours' behaviour, so that any impact of her neighbours' behaviour 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.

4.3 Dealing with the reflection issue

As underlined in Section 2, when correlated effects are properly dealt with, the other identification problem is the *reflection issue*. The reflection issue occurs because the endogenous effect is the mean outcome of the group and the individual behaviour is assumed to react linearly to individual characteristics. We deal with this identification issue by using a non-linear model, combined with exclusive averaging.[22]

Non-linear model. First, we use a Poisson fixed-effects model to deal with the count data nature of the explained variables. The Poisson count model being inherently non-linear ensues in

[22] As mentioned in Section 2, two other strategies have been put forward to deal with the reflection issue. The group intransitivity strategy cannot be applied here as we do not have access in the FLFS to the geolocation of dwellings, that would allow to compute individual-specific neighbours' averages. We do not implement a dynamic model with lagged social interaction variables as we cannot provide any theoretical justification to the lag in the transmission of endogenous and contextual effects applied to job search behaviours. Moreover, as the results will show, job search seems to follow a cyclical pattern, with a systematic decline in the third quarter of each year, which could bias estimates with lagged endogenous variables.

a non-linear relationship between the endogenous and contextual effects, as in other non-linear models analysed in the literature. As exposed in section 2.3, formal proofs of identification have been provided in the literature for the binary and multinomial models. A formal analysis of identification for count models is given in Houndetoungan (2022), who also uses exclusive averaging as we do.

Exclusive averaging. Second, our identification strategy also relies on exclusive averaging, which means that individual i is systematically excluded when computing local-neighbourhood averages for endogenous and contextual effects. Figure 3 below gives an illustrated understanding of the computation of contextual and endogenous effects. As presented in section 2.3, this strategy has been shown to provide identification in linear-in-means models by Boucher et al. (2014) and in binary outcomes models by Davezies et al. (2009). Boucher et al. (2014) show that it is necessary for exclusive averaging to provide that there is a sufficient number of groups of different sizes and identification is stronger if groups are of limited size. The number of neighbours used in our case to compute endogenous and contextual effects vary widely across individuals and are rather small, so that we believe our setting is well suited to use exclusive averaging for identification. We indeed have in the estimation sample 7,899 local neighbourhoods, of which total size vary between 1 and 78 individuals, with an average of 29 and a standard deviation of 11 (see Table 13 in Appendix). The number of employed neighbours vary between 0 and 54 individuals with an average of 14 and a standard deviation of 7, while the number of unemployed neighbours is on average 2 and can go up to a maximum of 15.

As previously mentioned, Houndetoungan (2022) considers exclusive averaging when analysing identification in a count model. However, we do not use the specific estimation method he developed and rather use the quasi-maximum likelihood method suited to estimate a Poisson count model with fixed effects (Wooldridge, 1999; Cameron and Trivedi, 2005).[23,24]

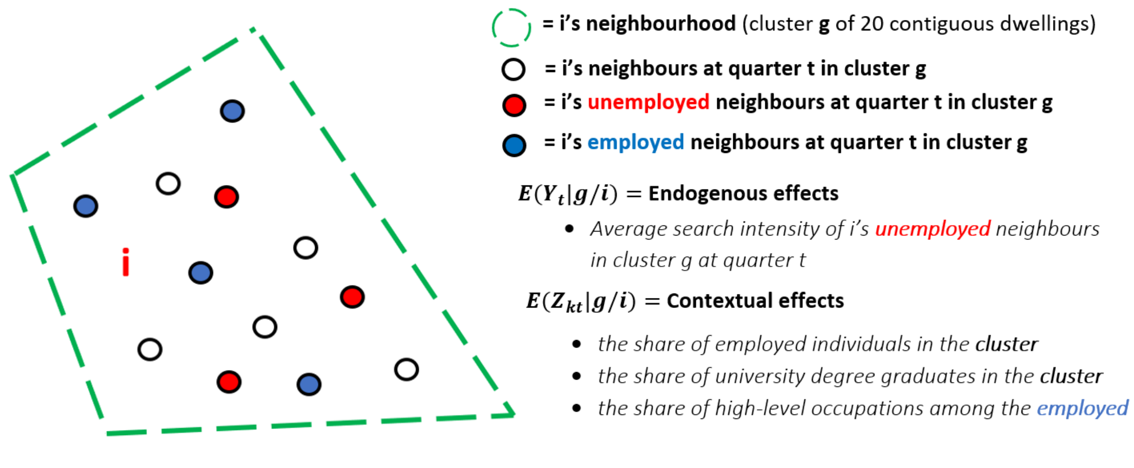

Figure 3: Computation of contextual and endogenous effects

[23] We consider that the explained variable in our analysis is not a discrete choice variable but rather, as also in Davezies et al. (2009), a continuous variable (how intensely an individual searches for a job through a given channel) observed as a discrete variable (how many times the individual answered yes to a set of questions on the job search in the FLFS).

[24] We may have considered the explained variables in our analysis as continuous and used the CML estimation proposed in Boucher et al. (2014) for a linear-in-means model, but Houndetoungan (2022) shows using Monte-Carlo simulations that ignoring the specificity of the count variable produces biased estimates. This is why we prefer to favour the count data nature of the outcomes we analyse.

Using different groups of neighbours. A final point relates to the definitions of endogenous and contextual effects and their consequences for identification. Indeed, we make a priori hypotheses as to the neighbours involved into the different social interaction effects, which contribute to identification.

Neighbours considered to compute the endogenous effects variable are all unemployed neighbours in the same cluster and same quarter as the individual. Considering unemployed neighbours only relies on the implicit assumption that there is no impact of the non-unemployed, i.e. employed or inactive, individuals' behaviour. This choice is justified by the fact that, as said previously, there is very little search by employed individuals. As shown in Figure 3, the endogenous effects correspond therefore to the average job search intensity linked to a particular job search channel (search through networks, through official employment organisations, through active and direct actions) or to the average total search intensity of other unemployed neighbours in the same cluster g at the same quarter t. While all unemployed neighbours are considered in doing so whatever their unemployment period, the estimation sample is restricted to individuals observed in their last unemployment period. This means that the same set of individuals as in the estimation sample is used to calculate the endogenous effect, but not necessarily in the same quarter as the one which is considered when they are included in the estimation sample.[25] For example, an individual with two successive unemployment periods included in the estimation sample at quarter t may be used to compute an endogenous effect at quarter $t-1$. As shown in Table 15 in the Appendix, only 43% of unemployed neighbours used for the computation of the endogenous effect at a particular quarter are also present at that particular quarter in the estimation sample.

The contextual effects correspond, for an unemployed individual i, to the characteristics that favour job search effort, averaged over neighbours present in the same cluster at the same quarter, i excluded. All surveyed neighbours are taken into account for the share of employed and university degree graduates neighbours. This means that neighbours included in the computation of these two contextual effects represent a larger set as compared to unemployed individuals part of the estimation sample. More precisely, while the estimation sample has 29,345 individuals, a total of 271,865 individuals are used to compute these two contextual effects. They therefore constitute a broader population within which unemployed individuals present in the estimation sample are swamped.[26] As for the share of neighbours in high-level occupations, all employed neighbours are taken into account, which naturally excludes the unemployed individuals in the estimation sample. Furthermore, these individuals being employed, they are not involved in the endogenous effect variable.

Because the sets of individuals considered in endogenous and contextual effects differ, there can not be perfect collinearity between endogenous and contextual effects. This results from the assumptions we make regarding the sources of endogenous and contextual effects. In particular, we assume that endogenous effects are due to unemployed individuals only because of the low rate of on-the-job-search, whereas the contextual effects are produced by a broader population and not restricted to unemployed individuals.[27] This second choice is justified by the neighbourhood effects literature which, as detailed in Section 2, underlines the specific characteristics of neighbours that favour a return to employment and may foster job search. We therefore end up with a non-canonical variant of Manski's model, with endogenous and contextual effects which are computed on different groups of neighbours, and contextual effects which are not simply the

[25] 57% of the unemployed individuals in this analysis face two or more unemployment spells.

[26] On average, unemployed individuals in the estimation sample represent only 8.8% of all individuals used to compute the two first contextual effects (cf Table 14 in Appendix).

[27] As previously said, unemployed individuals in the estimation sample represent only 8.8% of all individuals used to compute the first two contextual effects. Moreover, they are obviously not represented among employed individuals in clusters (see Table 14 in Appendix).

average of unemployed neighbours' characteristics. This drastically reduces the simultaneity in the behaviour of unemployed individuals considered in the endogenous effect and the behaviour of individuals used to compute the contextual effects.

Table 3: Definition of explanatory variables

Variables	**Definition**
% Employed	The share of employed neighbours among all individuals in each local neighbourhood, except individual i.
% High-level occupations	The share of high-level occupations among all employed individuals surveyed in each local neighbourhood.
% University graduates	The share of individuals with a university degree among all surveyed individuals in each local neighbourhood, except individual i.
Has UN Neighbours (0/1)	Having Unemployed Neighbours (0/1) is a dummy variable that equals to 1 if individual i has at least one unemployed neighbour in cluster g at quarter t, and 0 otherwise. It aims at simultaneously taking into account individuals for which endogenous effects are not computable and giving an insight on the perception of the unemployment status in the neighbourhood.
Av. search intensity	The average search intensity linked to one of the three job search channels (search through networks, through official employment organisations, through active and direct actions) or the average total search intensity of other unemployed individuals in a local neighbourhood (cluster). It corresponds to the endogenous effect in Manski's terminology.
HUN(0/1) x Endogenous	An interaction variable between the dummy Having Unemployed Neighbours (0/1) and the endogenous effect (average search intensity of other unemployed neighbours).
Top search intensity	The top/maximum job search intensity linked to one of the three job search channels (search through networks, search through official employment organisations, search through active and direct actions) or to total search intensity among other unemployed individuals in a local neighbourhood (cluster). It corresponds to another type of endogenous effect.
HUN(0/1) x Max Endogenous	An interaction variable between the dummy Having Unemployed Neighbours (0/1) and the endogenous effect in terms of maximum (top search intensity among other unemployed neighbours).
Age	Age of unemployed individuals. Age 15+: being aged between 29 and 30. Age 30+: being aged between 30 and 39. The reference for age in the regressions is being between 40 and 49 years old (Age 40+).
Education	Level of education of unemployed individuals. • Bac+3 schools: schools with a minimum level of bachelor degree that include the French Grandes Ecoles. • Associate degree: the French "*Diplôme d'études universitaires générales" (DEUG)* that corresponds to a second year of bachelor degree level. • Higher National Diploma (HND): the French "*Brevet de Technicien Supérieur" (BTS)* or "*Diplôme Universitaire Technologique" (DUT)* which are advanced vocational diplomas corresponding to a second year of bachelor degree level. • Paramedical/Social (Bac+2): paramedical and social studies equal to a second year of bachelor level. • General Baccalaureate: the general track of the French high-school diploma. It is the reference in the regressions. • Techn./Prof. Baccalaureate refers to two of the three tracks of the French high school diploma: the technical and professional Baccalaureate. • Vocational diploma: the French "*Certificat d'aptitude professionnelle" (CAP)* or "*Brevet d'études professionnelles" (BEP)* that allow to move towards the professional path directly after middle school.

Previous occupation	Previous occupation of unemployed individuals. Note that high-level occupations include senior executives and higher intellectual occupations (*cadres et professions intellectuelles supérieures*) and that independent workers include craftmen, shopkeepers and business owners. The reference for previous occupations is intermediate occupations.
Citizenship	Citizenship of unemployed individuals: French by birth (the reference in the regressions), French by naturalization or Foreigner.
Sex (female)	Sex of unemployed individuals: male (the reference) or female.
Child (0/1)	Having at least one child.
Quarter dummies	Quarter time dummies over the period of analysis: Q12014 to Q42019, to the exception of Q12016 which is the reference.

5 Results

Table 4 presents the main results of the estimation of equation 1 for each of the job search variables as outcome, while Table 16 in the Appendix presents the results for the control variables.

5.1 Main specification

Column (1) of Table 4 presents the results of our preferred specification for total search intensity. In terms of contextual effects, we find a positive and significant (at the 10 percent risk level) effect of the share of high-level occupations in a local neighbourhood. A one standard deviation increase in the share of high-level occupations in the neighbourhood increases total job search intensity by 0.042 units at the sample mean. This result seems to be mainly driven by search through networks with a (stronger and) more significant effect (Column (2)): a one standard deviation increase in the share of individuals in high-level occupations in a local neighbourhood raises search through networks by 0.024 units at the sample mean.[28] Indeed, it is easy to imagine that individuals in high-level occupations have information on job opportunities and a labour market network that facilitates job search. Crossing paths with one of these neighbours while being unemployed can indeed encourage job search, particularly via networks as they could very easily recommend an unemployed neighbour to one of their acquaintances.

Table 4: Main regression results

	Search intensity			
	Total search	Network search	Active and direct	Organisations
	(1)	(2)	(3)	(4)
Contextual effects				
% Employed	0.015	0.020	0.008	0.004
	(0.035)	(0.052)	(0.039)	(0.066)
% High-level occupations	0.061*	0.101**	0.046	0.003
	(0.036)	(0.049)	(0.044)	(0.073)
% University graduates	−0.045	−0.033	−0.034	−0.094
	(0.043)	(0.062)	(0.050)	(0.084)
Endogenous effects: Unemployed neighbours' av. search intensity				
Has UN Neighbours (0/1)	−0.082***	−0.142***	−0.031*	0.038*
	(0.017)	(0.020)	(0.017)	(0.021)
HUN (0/1) x Endogenous	0.024***	0.100***	0.022***	0.011
	(0.003)	(0.009)	(0.007)	(0.016)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Sector clustered SE	Yes	Yes	Yes	Yes
Log-likelihood	-56,744.59	-34,335.57	-39,711.53	-25,311.14
N (Obs., Sectors, Clusters)	29,345 & 2,645 & 7,899			
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4 presents sector fixed-effects regressions performed on the estimation sample as defined in the text. For a detailed explanation of all the independent variables, see Table 3.

[28] The calculation of the effect is based on the distribution of the contextual variables and the different job search variables (cf Tables 10 and 1 in the Appendix). For instance, for total search intensity, with mean job search intensity of unemployed individuals, the change in units after a one standard deviation increase in the share of high-level occupations $= \exp(0.061 \times 0.178) \times 3.9 - 3.9 = 0.042$.

Results in Column (1) of Table 4 also underline a simultaneous negative impact on total search intensity of having unemployed neighbours associated with a strong positive effects of their search intensity. Indeed, being the only unemployed in the neighbourhood involves a divergence from the main employment status in the neighbourhood and the need to conform to the social norm through a higher job search intensity, while having at least one unemployed neighbour lessens the social pressure of remaining unemployed. However, the more the unemployed neighbours search actively for work, the more an individual has incentives to search for a job. This implies that a minimum of job search intensity of unemployed neighbours is needed to counterbalance the (negative) impact of having unemployed neighbours. The results in Table 4 show that total search intensity increases by 0.015 units when going from having no unemployed neighbours to unemployed neighbours with mean job search intensity. If they instead have a job search intensity of 5 (corresponding to the third quartile of the endogenous variable distribution), then total search intensity increases by 0.038 units.[29] To overcome the negative impact of having unemployed neighbours, they need to search at an average intensity that is higher than 3.416, which corresponds to 62% of unemployed individuals in the sample.

Such findings suggest the existence of peer effects in job search behaviours both in terms of perception of the unemployment status in the neighbourhood and of unemployed peers' behaviours. On the one hand, if an unemployed individuals lives in a neighbourhood where he is the only unemployed and where the unemployment status is (unconciously) frowned upon, then he might face social pressure to find a job rapidly which increases job search intensity. On the other hand, if there are unemployed neighbours, individuals might also face social pressure to act similarly as others and to conform to the behaviours and social norms promoted within the neighbourhood, which is known as a place of socialisation. If an individual lives, for example, in a neighbourhood with many unemployed people who search very little, he or she might be tempted to do the same and to get involved in other activities. On the contrary, if an individual lives in a neighbourhood where on average unemployed individuals are actively looking for work, he or she should be encouraged by an imitation effect to do the same. These peer effects could also occur through the exchange of information between unemployed neighbours 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"*).

Strong and significant peer effects are also present for job search through networks (Table 4 Column (3)). Search through networks intensity decreases by 0.012 units when moving from having no unemployed neighbours to unemployed neighbours with mean job search intensity. If these neighbours instead have a job search intensity of 2 (corresponding to the third quartile of the endogenous variable distribution), then search through networks intensity increases by 0.058 units. To overcome the negative impact of having unemployed neighbours, the latter should search at an average intensity above 1.42, which corresponds to 41% of unemployed individuals in the sample.

We do not have any significant contextual effects for search through active and direct actions and search through employment organisations while endogenous effects are present but a bit less significant for active and direct search and absent for search through back-to-work organisations.

Estimated coefficients for endogenous effects in Column (3) show that active and direct search

[29] The total effect is computed based on the distribution (mean or Q3) of the endogenous job search variable in Table 11 in the Appendix. For instance, for total search intensity, with mean job search intensity of unemployed neighbours, the change in units is: $-0.082 + 0.024 \times 4.05 = 0.015$. With a Q3 job search intensity of unemployed neighbours, the change in units corresponds to: $-0.082 + 0.024 \times 5 = 0.038$.

intensity inscreases by 0.011 units when going from having no unemployed neighbours to unemployed neighbours with mean job search intensity. If they instead have a job search intensity of 2.6 (corresponding to the third quartile of the endogenous variable distribution), then active and direct search intensity increases by 0.026 units. To overcome the negative impact of having unemployed neighbours for this channel, they need to search at an average intensity that is higher than 1.41, which corresponds to 70% of individuals in the estimation sample. As shown by Table 4, search via back-to-work organisations is the job search channel that does not induce any endogenous peer effects. This is not surprising as it corresponds to the more "official" and traditional ways of finding a job. We can imagine that this type of job search is used more on an individual basis and leads to fewer social interaction effects as it is known to be less efficient. In contrast with the previous job search channels, having unemployed neighbours does not undermine job search through organisations. This is due to the fact that job search through this channel correspond to the minimal actions to be done when being unemployed, and therefore should not be hindered by the presence of other unemployed neighbours. It might also not be the preferred job search channel for unemployed individuals alone in their neighbourhood who want to find work quickly and efficiently.

Overall, the results for the main independent variables highlight the existence of social interaction effects in job search behaviours and more particularly for job search through networks, which corresponds to only 4 of the 21 questions related to job search and therefore seems to be driving the findings on total search. These endogenous and contextual effects indeed point to the existence of a social multiplier effect in job search behaviours and emphasise the importance of being surrounded by neighbours with strong labour market connections, that are likely to translate into unemployment inequalities across neighbourhoods. These results are consistent with what was observed by sociologists in the aforementioned survey *"Mon quartier, mes voisins"* that states that neighbourhood relationships remain at high levels in France and can play a role in job search via exchanges of information on job opportunities.

Answering the question of which social interaction effect is stronger is not straightforward. The coefficients of the endogenous effect variables seem to prevail in terms of significance. Moreover, the change in the share of high level occupations in the local neighbourhood needed to increase job search intensity would require a strong shift in the quality of the neighbourhood whereas the increase needed in the search intensity of unemployed neighbours seems more plausible.

A closer look at the effect of the individual characteristics, present in Table 16 in the Appendix, allows to account for the various determinants influencing job search. We comment on these control variables since they are rarely analysed in the literature. Regarding the search intensity linked to the use of networks, the higher the degree (Bachelor, Master, PhD level) or the more professionalizing the degree (Higher National Diploma or Technical Baccalaureate), the higher the network search intensity is. This is particularly true for individuals graduating from schools with a bac+3 (bachelor) minimum level (including the Grandes Ecoles) which are known in France as places of networking. Unemployed who have never worked or used to be low-level white collars or blue-collar workers before losing their job search less via networks, while unsurprisingly, this type of job search is favoured by unemployed in high-level occupations before losing their job. Also, being under 29-years favours research via social media, while women seem to search less via networks than men. Concerning the more active and direct way of searching, we observe a positive effect of being under 29 years old, of high-level or professionalizing diplomas (Higher National Diploma or Technical Baccalaureate) and of being a former low level white-collar. Having a child or being of foreign citizenship reduces job search through this channel, the same being true for unemployed who were independent workers i.e. craftmen, shopkeepers or business owners before losing their job. Indeed, being younger or having a higher or more professionalizing level of education favours more direct job search actions such as interviews, participation in trade fairs and job forums or responding to job offers. It can also be assumed that unemployed who were independent workers would favour a job search channel leading to entrepreneurship and to resettlement. Search intensity related to active contact with official employment organisations such as *"Pôle Emploi"* or temporary work agencies seems to be mainly used by individuals with less favourable characteristics regarding integration on the labour market. Indeed, as shown by the control variables, having short-term or low-level diplomas, being a former blue-collar worker or being foreigner foster search intensity through this channel which is, as previously mentionned, known as less efficient.

Regarding the time dummies, (not shown in the table), we find seasonal effects for the different job search variables. Individuals tend to search less during the third quarter which includes the summer holidays (July and August) and September in France.

5.2 Cross effects on job search variables

Table 5 displays a specification similar to the main specification to the exception that each job search channel intensity dependent variable (search through networks, active and direct search and search through organisations) is explained by the endogenous variable linked to the same channel and also to the other two channels. It can, among other features, give an indication on how the use of a particular job search channel interacts with the use of (similar or) different job search channels by unemployed neighbours.

As in the main specification, we find for search through networks and search through active and direct actions a simultaneous negative impact of having unemployed neighbours associated with a strong positive effects of their search intensity linked to the same channel, while finding no search through organisations own endogenous effect. What is new and very interesting here is that a high network search intensity of unemployed neighbours seems to be a booster not only for search through networks intensity but also for job search via the other two channels. An even more striking result is that, for active and direct search and for search through organisations, the endogenous effect related to networks is stronger in terms of both significance and magnitude than their specific endogenous effects.

For instance, active and direct search intensity inscreases by 0.004 units when we change from having no unemployed neighbours to unemployed neighbours with a Q3 job search through networks intensity against a decrease of 0.0272 units when we change from having no unemployed neighbours to unemployed neighbours with Q3 active and direct job search intensity. For search through organisations, we can see that there is no specific significant endogenous effect, while the network endogenous effect is positive and significant (at the 5% risk level).

Such findings may underline three different mechanisms: (i) neighbourhoods in which the unemployed search a lot via networks are neighbourhoods where individuals are generally very active in their job search (all channels combined); (ii) search via networks (at the individual and neighbourhood level) implies or has as consequences actions related to the two other job search channels; (iii) search via networks of unemployed neighbours could be a proxy of another phenomenon.

Table 5: Interaction with other channels

	Search intensity:		
	Network	Active	Organisations
	(1)	(2)	(3)
Contextual effects			
% Employed	0.020	0.011	0.005
	(0.052)	(0.039)	(0.066)
% High-level occupations	0.101**	0.043	−0.001
	(0.049)	(0.044)	(0.073)
% University graduates	−0.034	−0.040	−0.103
	(0.062)	(0.050)	(0.084)
Endogenous effects	Unemployed neighbours' av. search intensity		
Has UN Neighbours (0/1)	−0.142***	−0.050***	−0.002
	(0.023)	(0.018)	(0.028)
HUN (0/1) x Network endogenous	0.100***	0.027***	0.023**
	(0.010)	(0.006)	(0.009)
HUN (0/1) x Active endogenous	0.001	0.012*	0.007
	(0.008)	(0.007)	(0.009)
HUN (0/1) x Orga endogenous	−0.002	0.002	0.003
	(0.011)	(0.008)	(0.016)
Indiv. characteristics	Yes	Yes	Yes
Quarter time effects	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Sector clustered SE	Yes	Yes	Yes
Log-likelihood	-34,335.56	-39,702.14	-25,307.39
N (Obs., Sect., Clus.)	29,345 & 2,645 & 7,899		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5 presents sector fixed-effects regressions performed on the estimation sample as defined in the text. HUN(0/1) x Active endogenous, HUN(0/1) x Network endogenous and HUN(0/1) x Orga endogenous correspond respectively to the average search intensity of unemployed neighbours in a cluster linked to active actions leading to re-employment, to the use of networks and to search through employment organisations. For a detailed explanation of all the other independent variables, see Table 3.

6 Robustness checks

6.1 Location endogeneity issue

Test for the absence of sorting 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 neighbours' 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 neighbours' 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 run this test by first regressing both an individual's characteristic and the average of the same characteristic among neighbours on sector fixed effects.[30] The residuals of these two regres-

[30]Note that as for endogenous and contextual effects, the individual herself is removed when computing the

sions, which measure the deviations from the sector average, are then regressed on each other. The R-square of this regression measures the intensity of the correlation between these deviations from the sector average, and therefore the intensity of sorting on the chosen observable between clusters within sectors. This R-square is expected to be low. As explained in Bayer et al. (2008), it is useful to include in the estimation only one individual, randomly drawn, per cluster $\times$ quarter, in order to avoid a systematic negative correlation due to mean reversion.[31] For each of the chosen observed characteristics, this procedure is repeated 100 times each time on a different random sample.

The mean R-squares computed over these 100 repetitions are reported in Column (3) of Table 6 for 18 observed dummy variables describing education, previous occupation, citizenship and age. By way of comparison, Column (1) reports the same R-squares with no fixed effects (more precisely, R-squares of the regression of individual characteristics on neighbours average) and Column (2) reports the R-squares of the procedure with fixed effects at the commune level. The values in Column (1) are expected to be rather high due to spatial sorting at the neighbourhood level. Sorting between clusters within communes being still important, R-squares in Column (2) should still be significant, wherease R-squares in Column (3) are expected to be much lower. The results are presented in panel A of Table 6. Note that, to follow the definition of endogenous effects, neighbours taken into account in this test are all unemployed individuals in the same local neighbourhood and same quarter for each individual in the estimation sample, and the correlation is computed for individuals in the estimation sample.

The results of this test are convincing for a set of dummies, namely the lowest educational level, blue and white collar workers, French by naturalization and foreign citizenship, individuals aged below 30 and between 30 and 39. These dummy variables correspond to categories which are largely represented among the sample. More surprising results are obtained for graduates, intermediate profession, and the three categories of age above 30, for which R-squares increase when going from the unconditional regression to the regression with sector fixed effects. These odd results seem to be due to low shares of these categories in the population of unemployed individuals combined with the very low numbers of neighbours used for the computation of these shares. Indeed, Table 13 in Appendix shows that three quarters of the local neighbourhoods in the estimation sample have three unemployed individuals or less. These very low numbers might hinder a meaningful computation of the R-squares.

Therefore, we extend the test and use the same procedure to estimate the correlation between the observed characteristics of the individuals in the estimation sample and the set of all their neighbours aged over 15. This allows to test the hypothesis of random sorting on a larger number of neighbours and avoid the above mentioned small sample issue. If location within sectors into local neighbourhoods is indeed random, this should be seen in these correlations. The results for this extended test are presented in panel B in Table 6. This second set of results is totally in line with what is expected. For all of the categories, to the exception of the inactive category, a sharp decline in the average correlation is observed when one moves from the unconditional regression (Column (1)) to the regression controlling for sector averages (Column (3)). The values obtained for the mean R-squares of regression controlling for sector averages are except one of them below 0.01. We believe these tests to provide evidence that the identifying assumption we use to deal with location endogeneity is valid.

cluster average.

[31] Indeed, given that the individual is removed from the set of individuals used to compute the neighbours' average, within each neighbourhood high-level individuals are on average associated with low-level neighbours, and vice-versa.

Table 6: Correlation between individual and neighbours' average characteristics

	Fixed effects		
	None	Commune	Sector
Panel A: Unemployed neighbours			
Education			
None, primary or junior high-school	1.927	0.496	0.006
Vocational diploma	0.322	0.009	0.100
General baccalaureate	0.021	0.002	0.049
Graduate	0.001	0.065	0.328
Post-graduate	1.053	0.067	0.036
Previous occupation			
Inactive	0.011	0.008	0.066
Indep. worker	0.057	0.010	0.195
Executive	0.499	0.004	0.277
Intermediate prof.	0.014	0.032	0.310
Blue-/white-collar workers	0.778	0.143	0.043
Citizenship			
French	0.013	0.005	0.008
Fr. by naturalization	0.933	0.121	0.039
Foreign	3.974	1.229	0.020
Age			
< 30	0.232	0.057	0.002
30-39	0.203	0.015	0.057
40-49	0.001	0.041	0.247
50-59	0.017	0.055	0.284
$>= 60$	0.003	0.065	0.285
Panel B: All neighbours			
Education			
None, primary or junior high-school	9.622	3.479	0.199
Vocational diploma	3.800	0.139	0.027
General baccalaureate	0.893	0.119	0.015
Graduate	0.931	0.098	0.037
Post-graduate	22.23	5.387	0.165
Previous occupation			
Inactive	0.005	0.003	0.002
Indep. worker	0.202	0.036	0.008
Executive	14.12	3.513	0.223
Intermediate prof.	1.522	0.502	0.007
Blue-/white-collar workers	5.073	1.809	0.063
Citizenship			
French	28.79	10.52	1.133
Fr. by naturalization	7.213	2.439	0.159
Foreign	21.92	8.781	0.890
Age			
< 30	2.295	1.136	0.092
30-39	2.317	0.681	0.019
40-49	0.526	0.108	0.016
50-59	0.690	0.064	0.026
$>= 60$	0.928	0.478	0.061

Note: Estimations are run on the main estimation sample. R2 are expressed in percentages, so that 1.927 means that the RHS variable explains .019 percent of the LHS variable's variance. Panel A corresponds to results of the test in which the correlation is computed between the individuals' characteristics and that of their unemployed neighbours. Panel B corresponds to results of the tests in which the correlation is computed between the individuals' characteristics and that of all their neighbours aged above 15.

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.[32] Public housing units are owned by public housing offices, rented at below-market rents and most of them are built as large multi-family buildings. They house mostly low-income households, and the share of unemployed and low-skilled individuals in these dwellings is higher than in other parts of the housing stock. The poverty rate amounts indeed to 35% for public housing tenants, compared to 23% for private tenants and 7% for homeowners.[33] In terms of unemployment, 6.6% of public tenants are unemployed against 5.9% of private tenants and 2.2% of homeowners in 2020 (FLFS, own calculations).

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. Given the selection of households in the two parts of the housing stock, there could be some systematic variation in surveyed households in "public housing clusters" as compared to "private housing clusters". In other words, households would have chosen in which local neighbourhood to locate within a sector by getting access to a public housing unit, and the existence of a non-random location within sectors could affect the comparison between local neighbourhoods which is at the core of our strategy to deal with location endogeneity.

In order to check that there is no bias related to this issue in the estimates, we perform a robustness check which consists in removing from the estimation sample all clusters in which some housing units are public housing. In doing so, we keep clusters having only private housing, so that our identification strategy amounts to comparing clusters with no public housing within sectors. 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.

By doing so, the estimation sample is reduced by 40%, the number of sectors is reduced by 311, and 2285 local neighbourhoods, that is 29% of those present in the main sample, are discarded.

Results in Table 7 show a general stability with regards to the main specification especially for total search intensity and search through networks, which both correspond to the most interesting results of Section 5. The contextual effects linked to the share of high-level occupations are no longer significant for these two job search channels, but we have endogenous effects that are still very significant and heading in the same direction even if a bit less strong. Total search intensity increases by 0.0014 units (against 0.015 units on the main sample) when we change from having no unemployed neighbours to unemployed neighbours with mean job search intensity. If they instead have a job search intensity of 5.3 (corresponding to the 3rd quartile of the endogenous effect distribution on the new sample), then total search intensity increases by 0.0182 units (against 0,038 units before). To overcome the negative impact of having unemployed neighbours, they need to search at an average intensity that is higher than 4 which corresponds only to 57% of cases in the new sample (against 3.416 and 62% of cases on the estimation sample before). Search through networks intensity decreases by 0.0122 units (against 0.0120 units on the main sample) when we change from having no unemployed neighbours to unemployed neighbours with mean job search intensity. If they instead have a job search intensity of 2 (corresponding to the 3rd quartile of the endogenous effect distribution on the new sample), then search through networks intensity increases by 0.025 units (against 0.058 units on the main sample). To overcome the negative impact of having unemployed neighbours, they

[32] https://www.statistiques.developpement-durable.gouv.fr/le-parc-locatif-social-au-1er-janvier-2021
[33] https://www.insee.fr/fr/statistiques/3635547 - INSEE, 2018

need to search at an average intensity that is higher than 1.6 which corresponds only to 38% of cases in the new sample (against 1.42 and 41% of cases on the main sample before).

When discarding public housing clusters, we do not have anymore significant endogenous effect for active and direct search. As in the main specification, having unemployed neighbours does not undermine job search through organisations, but contrary to the main results, we have for this job search channel a negative endogenous effect. This negative effect can be explained by the fact that we keep for this robustness check only the unemployed outside public housing neighborhoods and who, of "better quality", may not favour this "less efficient" job search channel (contact and missions with temporary (interim) agencies, contact with *Pôle Emploi* etc.).

In summary, these additional results do not call into question the main results and show, particularly for total search intensity and search through networks, that they are not driven by the comparison between households belonging to the two segments of the housing market.

Table 7: Discarding public housing clusters - Robustness check

	Search intensity:			
	Total search	Network search	Active and direct	Organisations
	(1)	(2)	(3)	(4)
Contextual effects				
% Employed	0.017	−0.020	0.032	0.042
	(0.049)	(0.069)	(0.055)	(0.097)
% High-level occupations	0.072	0.076	0.072	0.059
	(0.046)	(0.060)	(0.055)	(0.098)
% University graduates	−0.029	0.036	−0.066	−0.112
	(0.057)	(0.081)	(0.066)	(0.114)
Endogenous effects: Unemployed neighbours' av. search intensity				
Has UN Neighbours (0/1)	-0.056^{***}	-0.099^{***}	0.003	0.061^{**}
	(0.022)	(0.025)	(0.022)	(0.028)
HUN (0/1) x Endogenous	0.014^{***}	0.062^{***}	0.002	-0.042^{*}
	(0.004)	(0.011)	(0.009)	(0.022)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Sector clustered SE	Yes	Yes	Yes	Yes
Log-likelihood	-32,687.68	-19,566.36	-22,592.31	-13,621.74
N (Obs., Sectors, Clusters)		17,590 & 2,334 & 5,614		
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7 presents sector fixed-effects regressions performed on the sample that discards public housing clusters. For a detailed explanation of all the independent variables, see Table 3.

6.2 Reflection issue

Using the max of neighbours instead of the mean. As explained in the literature review, the reflection issue is encountered in linear-in-means models. This suggests that a way to circumvent this issue is to consider other moments of the distribution of the endogenous effects. In our case, one can imagine that the maximum value of the job search intensity among neighbours could be what influence the individual's job search intensity. This consideration is particularly well suited given the count nature of the outcomes we analyse. In the following, we thus show results of estimations in which the endogenous effects is not the average neighbours' behaviour but its maximum value among them.

Before going on with the results, it seems important to compare the two types of endogenous effects and to outline their differences. The main difference between the two effects concerns their interpretation. While the mean endogenous effect shall be understood as a need for conformity to the average behaviour (social norm) promoted within the reference group (neighbourhood), the maximum endogenous effect shall be more understood as a role model effect according to which the behaviour of one individual is affected by the behaviours of "leaders" of the same social group. The first effect occurs through the comparison to the average behaviour in the group and is therefore more reciprocal, while the second occurs through the comparison to the "highest" behaviour in the reference group and the need to be "as good as".

Tables 18, 19, 20 and 21 in the Appendix compare the distribution of the mean endogenous effect and the maximum endogenous effect for each of the job search channels, with mean endogenous effects shown in categories for the sake of comparison. These figures show that there are indeed differences in distributions of the mean and maximum neighbours' behaviour, for each of the job search channels, with a maximum endogenous effect spread over several mean endogenous effect categories.[34] This reflects the variability of job search intensity among neighbours. Having in mind how these two endogenous effect are distinct from each other, we can now look at the estimation results presented in Table 8.

These results are very similar both in terms of coefficients and significativity to the results in Table 4. In terms of contextual effects, we again find a positive and significant effect of the share of high-level occupations in a local neighbourhood for total search intensity (at the 10 percent risk level) and search through networks (at the 5 percent risk level). A one standard deviation increase in the share of high-level occupations in the neighbourhood increases total job search intensity by 0.045 units at the sample mean (against 0.042 units before). A one standard deviation increase in the share of high-level occupations in the neighbourhood increases job search intensity through networks by 0.025 units at the sample mean (against 0.024 units before).

Results for maximum endogenous effects also head in the same direction than those related to mean endogenous effects. Similarly to the main specification, Table 8 underline, to again, the exception of search through back-to-work organisations, a simultaneous negative impact of having unemployed neighbours associated with a strong positive effects of their maximum search intensity. Total search intensity increases by 0.021 units when we change from having no unemployed neighbours to unemployed neighbours with a maximum job search intensity of 5 (corresponding to the mean of the maximum endogenous effect distribution). If they instead have a maximum job search intensity of 7 (corresponding to the 3rd quartile of the maximum endogenous effect distribution), then total search intensity increases by 0,061 units. To overcome the negative impact of having unemployed neighbours, they need to search at maximum intensity that is higher than 3.95, which corresponds to 76% of cases in our sample (against an average intensity higher than 3.416 and corresponding to 62% of cases). Search through networks intensity increases by 0.007 units when we change from having no unemployed neighbours to unemployed neighbours with a maximum job search intensity of 1.8 (corresponding to the mean of the maximum endogenous variable distribution). If they instead have a maximum job search intensity of 3 (corresponding to the 3rd quartile of the maximum endogenous effect distribution), then

[34] Table 18 for instance shows that 21% of unemployed who face a maximum total search endogenous effect of 6 in the local neighbourhood have a mean total search endogenous effect that varies between 3 and 4, 35% of them have a mean endogenous effect that varies between 4 and 5, 25% of them have a mean endogenous effect that varies between 5 and 6, while only 36% of them have a mean endogenous effect comprised between 6 and 7.

search through networks intensity increases by 0.097 units. To overcome the negative impact of having unemployed neighbours, they need to have a maximum job search intensity through networks that is higher than 1.71, which corresponds to 59% of cases in our sample (against an average intensity higher than 1.42 and corresponding to 41% of cases). Active and direct search intensity inscreases by 0.0165 units when we change from having no unemployed neighbours to unemployed neighbours with a maximum job search intensity of 2.5 (corresponding to the mean of the maximum endogenous variable distribution). If they instead have a maximum job search intensity of 3 (corresponding to the 3rd quartile of the maximum endogenous effect distribution), then active and direct search intensity increases by 0.027 units. To overcome the negative impact of having unemployed neighbours, they need to search at a maximum intensity that is higher than 1.71, which corresponds to 79% of cases in our sample (againt an average intensity higher than 1.41 and corresponding to 70% of cases). As in Table 4, search via back-to-work organisations is the only job search channel that is not undermined by the presence of other unemployed neighbours and that does not induce any endogenous maximum peer effects.

Overall, the stability of the results between the endogenous effects in average and the endogenous effects in maximum seem to underline that our empirical strategy controls well for the reflection issue.

Table 8: Maximum search regression results - variables of interest

	Search intensity:			
	Total search	Network search	Active and direct	Organisations
	(1)	(2)	(3)	(4)
Contextual effects				
% Employed	0.026	0.039	0.015	0.005
	(0.035)	(0.053)	(0.039)	(0.066)
% High-level occupations	0.064*	0.107**	0.048	0.003
	(0.037)	(0.050)	(0.044)	(0.074)
% University graduates	−0.044	−0.027	−0.035	−0.096
	(0.043)	(0.063)	(0.050)	(0.084)
Endogenous effects: Unemployed neighbours' top search intensity				
Has UN Neighbours (0/1)	−0.079***	−0.128***	−0.036**	0.046**
	(0.016)	(0.020)	(0.017)	(0.021)
HUN (0/1) x Max Endogenous	0.020***	0.075***	0.021***	0.001
	(0.003)	(0.008)	(0.006)	(0.012)
Indiv. characteristics	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Log-likelihood	-56,746.84	-34,357.72	-39,709.99	-25,311.47
N (Obs., Sectors, Clusters)	29,345 & 2,645 & 7,899			
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 8 presents 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 neighbours linked to a particular job search channel. For a detailed explanation of all the independent variables, see Table 3.

7 Discussion

It seems important to discuss two potential limits to this analysis. With the sector fixed-effects in equation 1, we are comparing unemployed individuals part of the same sector but not surveyed at the same time i.e. over possibly 5 years in the estimation sample.[35] This means that we use as *control group* unemployed individuals who live in the same sector but at different time scales, which might raise two issues. The main question is: are the unemployed individuals surveyed at $t = 0$ good control groups for unemployed individuals surveyed at $t = 5$? That is, could there be systematic variations in neighbourhood "quality"? This also raises a question of time varying-shocks that could be specific to some local neighbourhoods. Examples of time-varying shocks include the closure of a factory in a specific local neighbourhood that could create more local unemployment or 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 local neighbourhood.

To answer the first point, it is important to consider the nature of the evolution that would make all the unemployed individuals in the same sector present in the estimation sample incomparable over time, and therefore not good control groups. To that end, there would need to be a systematic change between the beginning and the end of the period (2014-2019) that would go in the same direction in each of the sector present in the estimation sample and that would affect both the outcome variables (the different job search variables) and the quality of the unemployed individuals, which seems highly unlikely.

To address the second point, we implement for each of the job search variables a specification with clustered robust standard errors at the local neighbourhood (cluster) level. While the literature shows that determining the appropriate level of clustering is not straightforward (Bertrand et al., 2004; MacKinnon, Nielsen, and Webb, 2020), implementing, in our case, regressions with clustered robust standard errors at the local neighbourhood level allows us to take into account the fact that the errors of individuals located in the same cluster (over a maximum of one year and a half - six quarters) are correlated as they are subject to the same shocks. This second specification is presented in Table 17 in the Appendix.

Clustering the standard errors at the local neighbourhood level increases the standard errors and decreases the significance of coefficients. This lower level of clustering increases slightly the contextual effects' standard errors with the effect of the share of neighbours in high-level occupations which becomes not significant for total search intensity and search through networks. Endogenous effects for total search intensity, search through networks and active and direct search are still strong and significant, while the dummy having unemployed neighbours is not significant anymore for search through organisations and active and direct search. We therefore still have important endogenous peer effects in job search behaviours after the control for time-varying shocks with a lower level of clustering. [36]

It is important to underline that with the job search variables that we are computing with the FLFS, we are studying search intensity linked to different job search channels rather than search

[35] Individuals in the same sector can be surveyed over the period going from the first quarter of 2014 to the fourth quarter of 2019.

[36] Another way to deal with these time-varying shocks would be to use a approach similar to Hémet and Malgouyres (2018), who define a strategy where they use fixed-effects on pairs of local neighbourhoods surveyed in succession. We tried to implement a similar strategy in our analysis but faced a selection issue given that this strategy required the presence of at least one unemployed individual in both the last wave of a local neighbourhood and the first wave of a second time-adjacent local neighbourhood. This resulted in the selection of subsectors of "lower quality" unemployed individuals and the restriction to neighbourhoods with a high-level of unemployed individuals.

efficiency or search quality i.e. whether it lead to a success in employment. We are well aware from the literature that some job search channels are more effective than others (Montgomery, 1991; Granovetter, 1995; Caliendo et al., 2011; Cingano and Rosolia, 2012), however, in this paper, we focus on how unemployed individuals search for work (channels, intensity) rather than on the efficiency of these various methods.

Another important point to mention is that as our sample of analysis selects unemployed individuals defined according to the ILO conditions, we focus in this paper on the intensive margin of job search rather than on its extensive margin. We are interested in the job search behaviours of unemployed individuals i.e. whether they remain passive (no job search) or do search (level of intensity) and how (channels used). We do not focus here on questions regarding participation on the labour market i.e. whether individuals declare themselves as unemployed and therefore search or not.

8 Conclusion

This paper aims at detecting and measuring the importance of interactions with neighbours in the job search behaviours of unemployed individuals, both in terms of channels used and intensity, which we know, play a central role in return to employment and labour market outcomes. We use data from the French Labour Force Survey (INSEE) that allows us to (i) identify various job search channels including search through employment organisations, search through active and direct actions and search through networks and (ii) identify two nested levels of neighbourhoods at a very thin and precise level, through the existence of clusters of 20 contiguous dwellings grouped into sectors.

We delve into in the questions of social interactions through the implementation of a model of endogenous (how the average behaviour of neighbours impacts individual behaviour) and contextual effects (how neighbours' characteristics impact individual behaviour) à la Manski (1993), applied to the different job search channels. We tackle the reflection issue that deals with the separate econometric identification of endogenous and contextual effects through the use of non-linear estimation techniques and specific computational methods for the social interaction variables. We control for the location endogeneity issue that deals with the non-random sorting of individuals into neighbourhoods in a similar way than in Bayer et al. (2008), with the inclusion of sector fixed-effects that induce that once controlled for a higher level of location (sector), location within clusters (local neighbourhoods) can be considered as exogenous.

We contribute to the literature by underlining the presence of social interaction effects in job search behaviours. We find important endogenous effects for two out of the three job search channels we consider and for total search intensity. We underline a simulataneous negative impact of having unemployed neighbours counterweighted by a strong positive effect of their search intensity. Such findings suggest the existence of peer effects in job search behaviours both in terms of perception of the unemployment status in the neighbourhood and of unemployed peers' behaviours. If having unemployed neighbours reduces the social pressure of remaining unemployed and diminishes search intensity, this changes when they search actively for work. The latter mechanism translates into a social multiplier effect: the more unemployed neighbours search through a specific channel, the higher the incentives to act similarly. They can either be explained by social pressure in non-deviating from the job search behaviours promoted within the neighbourhood or through a spread of information between peers that reduces the costs associated to job search. We also find some contextual effects linked to the share of neighbours in high-level occupations for total search intensity and search through networks, that however disappear with a lower level of standard errors clustering. This highlight that interactions with neighbours highly connected to the labour market are important regarding access to information on job opportunities.

More important, the social interactions results for search through networks are central to this paper, especially if we link them to the literature that shows that it is the most effective job search channel (Montgomery, 1991; Granovetter, 1995; Caliendo et al., 2011; Cingano and Rosolia, 2012). This would therefore mean that living in a neighbourhood where unemployed individuals actively search through networks and where we have an increasing share of high-level occupations through time not only fosters job search through networks but might also lead more rapidly to a return on the labour market. It is perhaps here via the job search through networks findings that we can highlight how the existence of social interaction effects related to job search behaviours (channels, intensity) within the neighbourhood can translate into unemployment inequalities across neighbourhoods. Endogenous effects indeed reinforce favourable or less favourable behaviours related to job search across different types of neighbourhoods, while neighbourhoods with poorer quality of social networks may suffer from higher unemployment rates as their residents would have less connections to the labour market and exert lower levels of the very efficient job search through networks channel.

The social interactions results for the *à priori* more efficient 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 labour 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 neighbourhood, 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.

Further research would nonetheless be necessary to address the gap in the literature linking the existence of social interactions effects in job search behaviours to the literature underlining the efficiency of different job search channels in return to employment, in understanding urban unemployment inequalities.

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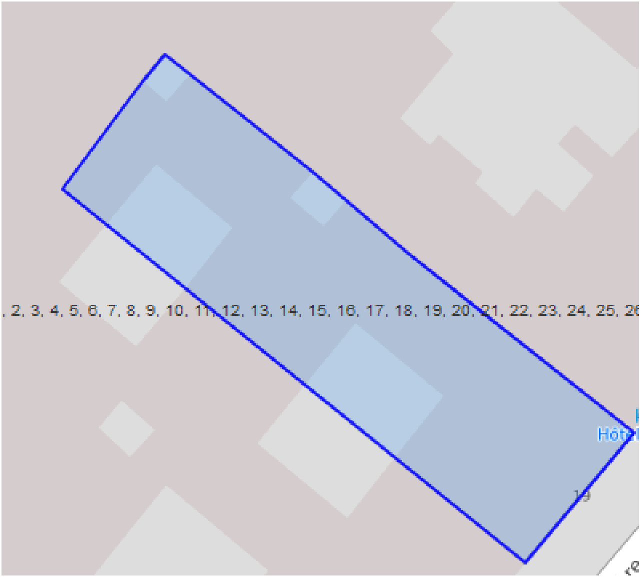
Appendices

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

Figure 4: Example of a cluster in Paris - 28 dwellings part of the same building



Source: INSEE

Figure 5: Example of a cluster in a rural community

Source: INSEE

B. Computation of the job search variables

Figure 6: The FLFS questionnaire and job search related questions

Search through organisations		
Questions: In the past four weeks...	**Yes**	**No**
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*), a placement operator, 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?		
Q3: Have you done some missions with a temporary employment agency (interim)?		
Active and direct search		
Questions: In the past four weeks...	**Yes**	**No**
Q1: Have you had a test or an interview for a job?		
Q2: Did you take part in an entry test for civil service?		
Q3: 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?		
Q4: 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?		
Q5: Have you been to a professional fair or a job forum?		
Q6: Have you reviewed some job advertisements?		
Q7: Have you responded to a job advertisement/offer?		
Search through networks		
Questions: In the past four weeks...	**Yes**	**No**
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?		
Q4: Have you had a job advertisement placed or posted, for example in a newspaper or on the internet?		
Search leading to entrepreneurship		
Questions: In the past four weeks...	**Yes**	**No**
Q1: Have you tried to take over a company, a business or an established practice?		
Q2: Have you been looking for land, premises or equipment?		
Q3: Did you seek financial resources (bank loans, public grants, etc.)?		
Q4: Have you applied for a permit, a licence or an authorisation to set up a business?		
Passive search		
Questions: In the past four weeks...	**Yes**	**No**
Q1: Have you been waiting for the results of previous attempts/procedures (test, Interviews, etc.)?		
Q2: Have you been waiting for a call from Pôle Emploi, a placement operator or a job placement association?		
Q3: Have you been waiting for the result of an entry test for civil service?		
Total search intensity		

Figure 7: An example for the computation of the job search variables

Search through organisations		
Questions: In the past four weeks...	**Yes**	**No**
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*), a placement operator, the chamber of commerce and industry or any other public institute?	X	
Q2: Have you contacted one (or more) temporary employment (interim) agencies or a placement operator?		X
Q3: Have you done some missions with a temporary employment agency (interim)?		X
Total	1	
Active and direct search		
Questions: In the past four weeks...	**Yes**	**No**
Q1: Have you had a test or an interview for a job?	X	
Q2: Did you take part in an entry test for civil service?		X
Q3: 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?		X
Q4: 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?		X
Q5: Have you been to a professional fair or a job forum?		X
Q6: Have you reviewed some job advertisements?	X	
Q7: Have you responded to a job advertisement/offer?	X	
Total	3	
Search through networks		
Questions: In the past four weeks...	**Yes**	**No**
Q1: Have you turned to personal contacts such as family or friends to find a job or set up a business?	X	
Q2: Have you turned to professional contacts to find a job or set up a business?	X	
Q3: Have you shared via digital social networks that you are looking for a job, and made your professional profile known?		X
Q4: Have you had a job advertisement placed or posted, for example in a newspaper or on the internet?		X
Total	2	
Search leading to entrepreneurship	0	
Passive search	0	
Total search intensity	6	

C. Descriptive statistics

Table 9: Distribution of the job search variables (explanatory variables) on the different samples

Search intensity	Min	Q1	Median	Mean	Q3	Max	SD
Estimation sample	29,345 obs. & 2,645 sectors & 7,899 clusters						
Total	0	2	4	3.9	6	15	2.4
Network	0	0	1	1.3	2	4	1.2
Active and Direct	0	1	2	1.9	3	6	1.2
Organisations	0	0	1	0.7	1	3	0.8
Without social housing clusters sample	17,590 obs. & 2,334 sectors & 5,614 clusters						
Total	0	2	4	4	6	15	2.4
Network	0	0	1	1.3	2	4	1.2
Active and Direct	0	1	2	1.9	3	6	1.3
Organisations	0	0	1	0.7	1	3	0.8

* Total refers to the total search intensity of individuals. Network to the search intensity linked to the use of networks and Active and direct to direct and active actions leading to re-employment. Organisations to the search intensity linked to employment organisations.

Table 10: Distribution of contextual variables on the different samples

	Min	Q1	Median	Mean	Q3	Max	SD
Estimation sample	29,345 obs. & 2,645 sectors & 7,899 clusters						
% Employed	0	0.364	0.478	0.473	0.581	1	0.157
% High-level occupations	0	0	0.100	0.151	0.227	1	0.178
% University degree	0	0.111	0.208	0.246	0.333	1	0.182
Without social housing clusters sample	17,590 obs. & 2,334 sectors & 5,614 clusters						
% Employed	0	0.406	0.50	0.504	0.604	1	0.149
% High-level occupations	0	0.589	0.15	0.199	0.292	1	0.19
% University degree	0	0.167	0.265	0.303	0.40	1	0.184

* Employed and University degree refer to the average share of employed and university degree graduates in a cluster (local neighbourhood). High-level occupations corresponds to the share of senior executives and higher intellectual occupations (*cadres et professions intellectuelles supérieures*) among the employed workers of a cluster (local neighbourhood).

Table 11: Distribution of endogenous variables on the different samples

Endogenous (Av. search intensity)	Min	Q1	Median	Mean	Q3	Max	SD	NA
Estimation sample	29,345 obs. & 2,645 sectors & 7,899 clusters							
Total	0	3	4	4.05	5	15	1.84	7,724
Network	0	0.5	1	1.3	2	4	0.97	7,724
Active and Direct	0	1.1	2	1.9	2.6	6	0.95	7,724
Organisations	0	0	0.8	0.8	1	3	0.63	7,724
Without social housing clusters sample	17,590 obs. & 2,334 sectors & 5,614 clusters							
Total	0	3	4	4.1	5.3	15	1.9	5,930
Network	0	0.7	1	1.4	2	4	1.02	5,930
Active and Direct	0	1	2	1.96	3	6	1.03	5,930
Organisations	0	0	0.7	0.7	1	3	0.66	5,930

* Av. search intensity refers to the average search intensity of unemployed neighbours in a cluster. It corresponds to the endogenous effect in Manski's terminology. In this table, the endogenous effect is presented for each of the job search channels. Total refers to the total search intensity of individuals. Network to the search intensity linked to the use of networks and Active and direct to direct and active actions leading to re-employment. Organisations to the search intensity linked to employment organisations.

Table 12: Decile distribution of endogenous variables on the different samples

Endogenous (Av. search intensity)	D1	D2	D3	D4	D5	D6	D7	D8	D9	NA
	10%	20%	30%	40%	50%	60%	70%	80%	90%	
Estimation sample	29,345 obs. & 2,645 sectors & 7,899 clusters									
Total	2	2.5	3	3.5	4	4.4	5	5.5	6.5	7,724
Network	0	0.5	0.8	1	1	1.5	2	2	2.75	7,724
Active and Direct	1	1	1.5	1.75	2	2	2.5	3	3	7,724
Organisations	0	0	0.33	0.5	0.75	1	1	1	1.6	7,724
Without social housing clusters sample	17,590 obs. & 2,334 sectors & 5,614 clusters									
Total	1.67	2.5	3	3.5	4	4.5	5	6	7	5,930
Network	0	0.5	1	1	1	1.5	2	2	3	5,930
Active and Direct	0.75	1	1.4	1.8	2	2	2.5	3	3	5,930
Organisations	0	0	0	0.5	0.67	1	1	1	1.67	5,930
All unemployment spells sample	69,045 obs. & 2,645 sectors & 7,899 clusters									
Total	2	2.67	3	3.5	4	4.4	5	5.5	6.5	15,429
Network	0	0.5	0.8	1	1	1.5	2	2	2.67	15,429
Active and Direct	1	1	1.5	1.75	2	2	2.5	3	3	15,429
Organisations	0	0	0.43	0.5	0.78	1	1	1.17	1.67	15,429

* Av. search intensity refers to the average search intensity of unemployed neighbours in a cluster. It corresponds to the endogenous effect in Manski's terminology. In this table, the endogenous effect is presented for each of the job search channels. Total refers to the total search intensity of individuals. Network to the search intensity linked to the use of networks and Active and direct to direct and active actions leading to re-employment. Organisations to the search intensity linked to employment organisations.

Table 13: Number of individuals, employed individuals and unemployed individuals by local neighbourhood

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	SD
# individuals	1	21	28	28.9	36	78	11.1
# employed	0	8	13	13.7	18	54	7.4
# unemployed	1	1	2	2.3	3	15	1.5
Observations				7,899			

These figures describe the distribution of the number of all individuals aged over 15, of employed individuals and of unemployed individuals for the 7,899 local neighbourhoods present in the estimation sample. They contribute to the understanding of how the different groups used to compute the endogenous and contextual effects vary in terms of size.

Table 14: Share of unemployed in the computation of contextual effects

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	SD
			among all individuals in the cluster				
% Unemployed	1.6	4.4	7.1	8.8	11.1	100	6.7
			among all university degree graduates in the cluster				
% University graduates unemployed	0	0	0	8.5	12.5	100	14.5
Sample			7,899 obs. & 2,645 sectors & 7,899 clusters				

* Table 14 gives the distribution of the share of unemployed and university degree graduates unemployed among all the individuals and all university degree graduates individuals of local neighbourhoods present in the estimation smaple. It aims at understanding how unemployed are swamped into a broader population used to compute two of the three contextual effects.

Table 15: N unemployed neighbours used to compute endogenous effects and present in the estimation sample

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	SD	NA
% present in the estimation sample	0	0	33.3	43.3	100	100	44.8	7,724
Estimation sample			29,345 obs. & 2,645 sectors & 7,899 clusters					

* For each of the unemployed individual present in the estimation sample at their last unemployment spell, we check if the unemployed neighbours used to compute the endogenous effect are also present at that specific quarter in the estimation sample. Only 43.3 % of unemployed individuals used to compute the endogenous effect at a specific quarter are also present at that same quarter in the estimation sample.

D. Main specification: control variables results and results with a lower level of SE clustering

Table 16: Main specification results - control variables

	Search intensity:			
	Total search	Network search	Active and direct	Organisations
	(1)	(2)	(3)	(4)
Age				
Age 15+	0.067***	0.033**	0.087***	0.101***
	(0.011)	(0.016)	(0.013)	(0.021)
Age 30+	0.002	−0.009	0.004	0.009
	(0.011)	(0.016)	(0.013)	(0.020)
Age 40+	Ref.	Ref.	Ref.	Ref.
Age 50+	−0.060***	−0.019	−0.061***	−0.140***
	(0.012)	(0.018)	(0.014)	(0.023)
Age 60+	−0.266***	−0.156***	−0.281***	−0.424***
	(0.022)	(0.030)	(0.024)	(0.045)
Education				
Bachelor, Master, PhD	0.100***	0.168***	0.072***	0.038
	(0.018)	(0.025)	(0.020)	(0.034)
Bac+3 schools	0.095***	0.192***	0.032	−0.029
	(0.026)	(0.034)	(0.030)	(0.052)
Associate degree	0.024	0.070	0.002	0.051
	(0.043)	(0.062)	(0.047)	(0.079)
Higher National Diploma	0.113***	0.137***	0.088***	0.148***
	(0.018)	(0.026)	(0.020)	(0.035)
Paramedical/Social (Bac+2)	−0.001	0.047	−0.025	−0.118
	(0.043)	(0.063)	(0.048)	(0.094)
General baccalaureate	Ref.	Ref.	Ref.	Ref.
Techn./Prof. Baccalaureate	0.084***	0.093***	0.060***	0.141***
	(0.016)	(0.024)	(0.018)	(0.031)
Vocational diploma	0.022	0.027	−0.006	0.110***
	(0.016)	(0.023)	(0.018)	(0.030)
Middle School Certificate	−0.020	−0.021	−0.044**	0.069*
	(0.019)	(0.029)	(0.021)	(0.036)
Primary School Certificate	−0.139***	−0.124**	−0.139***	−0.105
	(0.035)	(0.057)	(0.037)	(0.068)
No diploma	−0.078***	−0.072***	−0.113***	0.030
	(0.017)	(0.024)	(0.019)	(0.032)
NA (Education)	0.059	0.118**	−0.007	0.146**
	(0.038)	(0.053)	(0.044)	(0.066)
Previous occupation				
Farmers	−0.447***	−0.471*	−0.295*	−1.113***
	(0.166)	(0.250)	(0.176)	(0.341)
Independent workers	−0.065***	−0.080**	−0.142***	−0.030
	(0.025)	(0.033)	(0.030)	(0.045)
High-level occupations	0.039**	0.118***	0.0001	−0.121***
	(0.017)	(0.022)	(0.020)	(0.036)
Intermediate occupations	Ref.	Ref.	Ref.	Ref.
Low level white-collars	−0.015	−0.067***	0.023*	−0.008
	(0.012)	(0.017)	(0.013)	(0.024)
Blue-collar workers	−0.041***	−0.131***	−0.057***	0.147***
	(0.013)	(0.018)	(0.014)	(0.023)
Unemployed (never worked)	−0.155***	−0.259***	−0.078***	−0.161***

	(0.014)	(0.021)	(0.015)	(0.028)
Others (N.A)	−0.049	−0.072	−0.068	0.056
	(0.037)	(0.051)	(0.042)	(0.063)
Citizenship				
French (naturalization)	0.038**	0.048**	0.005	0.111***
	(0.015)	(0.022)	(0.017)	(0.028)
Foreigner	0.001	0.039**	−0.057***	0.095***
	(0.013)	(0.018)	(0.014)	(0.021)
French (birth)	Ref.	Ref.	Ref.	Ref.
NA (nationality)	−0.328	0.037	−0.548*	−0.725
	(0.244)	(0.245)	(0.287)	(0.711)
Sex (female)	−0.056***	−0.074***	0.012	−0.173***
	(0.008)	(0.011)	(0.009)	(0.015)
Child (0/1)	−0.020**	0.004	−0.029***	−0.061***
	(0.008)	(0.012)	(0.010)	(0.015)
Quarter dummies	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Sector clustered SE	Yes	Yes	Yes	Yes
Log-likelihood	-56,744.59	-34,335.57	-39,711.53	-25,311.14
N (Obs., Sectors, Clusters)	29,345 & 2,645 & 7,899			
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 16 presents sector fixed-effects regressions on the estimation sample. For a detailed explanation of all the independent variables, see Table 3.

Table 17: Main regression results with a lower level of SE clustering

	Search intensity							
	Total search		Network search		Active and direct		Organisations	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Clustered SE	S	LN	S	LN	S	LN	S	LN
Contextual effects								
% Employed	0.015	0.015	0.020	0.020	0.008	0.008	0.004	0.004
	(0.035)	(0.123)	(0.052)	(0.180)	(0.039)	(0.141)	(0.066)	(0.236)
% High-level occupations	0.061*	0.061	0.101**	0.101	0.046	0.046	0.003	0.003
	(0.036)	(0.048)	(0.049)	(0.067)	(0.044)	(0.056)	(0.073)	(0.096)
% University graduates	−0.045	−0.045	−0.033	−0.033	−0.034	−0.034	−0.094	−0.094
	(0.043)	(0.063)	(0.062)	(0.090)	(0.050)	(0.074)	(0.084)	(0.120)
Endogenous effects: Unemployed neighbours' av. search intensity								
Has UN Neighbours (0/1)	−0.082***	−0.082***	−0.142***	−0.142***	−0.031*	−0.031	0.038*	0.038
	(0.017)	(0.024)	(0.020)	(0.032)	(0.017)	(0.026)	(0.021)	(0.039)
HUN (0/1) x Endogenous	0.024***	0.024***	0.100***	0.100***	0.022***	0.022***	0.011	0.011
	(0.003)	(0.003)	(0.009)	(0.009)	(0.007)	(0.006)	(0.016)	(0.015)
Indiv. characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-56,744.59		-34,335.57		-39,711.53		-25,311.14	
N (Obs., Sectors, Clusters)	29,345 & 2,645 & 7,899							
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 17 presents sector fixed-effects regressions performed on the estimation sample. Model (1) implements clustered robust standard errors at the sector (S) level while model (2) implements clustered robust standard errors at the local neighbourhood (LN) level. For a detailed explanation of all the independent variables, see Table 3.

E. Comparison of the endogenous variable in mean vs. the endogenous variable in maximum

Table 18: Repartition: Total search intensity Mean vs. Max Endogenous

Mean	0	0 to 1	1 to 2	2 to 3	3 to 4	4 to 5	5 to 6	6 to 7	7 to 8	8 to 9	9 to 11	>11	NA	Total
Max														
0	619	0	0	0	0	0	0	0	0	0	0	0	0	619
1	0	61	609	0	0	0	0	0	0	0	0	0	0	670
2	0	13	330	1074	0	0	0	0	0	0	0	0	0	1,417
3	0	2	219	682	1454	0	0	0	0	0	0	0	0	2,357
4	0	1	45	695	1008	1582	0	0	0	0	0	0	0	3,331
5	0	0	10	370	1089	981	1346	0	0	0	0	0	0	3,796
6	0	0	2	132	769	997	709	1025	0	0	0	0	0	3,634
7	0	0	1	43	347	683	670	348	734	0	0	0	0	2,826
8	0	0	0	13	91	367	420	343	177	363	0	0	0	1,774
9	0	0	0	2	32	94	204	181	116	74	165	0	0	868
10	0	0	0	0	3	12	28	50	45	47	64	0	0	249
11	0	0	0	0	4	2	5	15	9	12	10	6	0	63
12	0	0	0	0	0	0	0	1	2	3	0	5	0	11
13	0	0	0	0	0	0	0	0	0	1	1	1	0	3
14	0	0	0	0	0	0	0	0	0	0	0	1	0	1
15	0	0	0	0	0	0	0	0	0	1	0	1	0	2
NA	0	0	0	0	0	0	0	0	0	0	0	0	7,724	7,724
Total	619	77	1,216	3,011	4,797	4,718	3,382	1,963	1,083	501	240	14	7,724	29,345

* Table 18 gives the distribution of observations in categories of the total job search endogenous variable in mean (average search intensity of unemployed neighbours in a cluster) versus the distribution of the total job search endogenous variable in maximum (maximum search insity among unemployed neighbours in the cluster) on the estimation sample.

Table 19: Repartition: Search through networks intensity Mean vs. Max Endogenous

Mean	0	0 to 0.5	0.5 to 1	1 to 1.5	1.5 to 2	2 to 2.5	2.5 to 3	3 to 3.5	3.5 to 4	NA	Total
Max											
0	3,483	0	0	0	0	0	0	0	0	0	3,483
1	0	1,784	3,516	0	0	0	0	0	0	0	5,300
2	0	138	2,029	1,686	2,846	0	0	0	0	0	6,699
3	0	6	280	931	1,138	733	1,360	0	0	0	4,448
4	0	0	21	70	308	307	348	194	443	0	1,691
NA	0	0	0	0	0	0	0	0	0	7,724	7,724
Total	3,483	1,928	5,846	2,687	4,292	1,040	1,708	194	443	7,724	29,345

* Table 19 gives the distribution of observations in categories of the job search through netwoks endogenous variable in mean (average search intensity of unemployed neighbours in a cluster) versus the distribution of the job search through networks endogenous variable in maximum (maximum search insity among unemployed neighbours in the cluster) on the estimation sample.

Table 20: Repartition: Active and direct search Mean vs. Max Endogenous

Mean / **Max**	0	0 to 0.5	0.5 to 1	1 to 1.5	1.5 to 2	2 to 2.5	2.5 to 3	3 to 3.5	3.5 to 4	4 to 4.5	>4.5	NA	Total
0	1,191	0	0	0	0	0	0	0	0	0	0	0	1,191
1	0	429	2,868	0	0	0	0	0	0	0	0	0	3,297
2	0	9	774	1,519	3,016	0	0	0	0	0	0	0	5,318
3	0	0	86	841	2,268	1,616	3,006	0	0	0	0	0	7,817
4	0	0	12	90	583	844	881	497	897	0	0	0	3,804
5	0	0	0	1	11	22	40	27	38	13	39	0	191
6	0	0	0	0	0	0	1	1	0	0	1	0	3
NA	0	0	0	0	0	0	0	0	0	0	0	7,724	7,724
Total	1,191	438	3,740	2,451	5,878	2,482	3,928	525	935	13	40	7,724	29,345

* Table 20 gives the distribution of observations in categories of the active and direct job search endogenous variable in mean (average search intensity of unemployed neighbours in a cluster) versus the distribution the active and direct job search endogenous variable in maximum (maximum search intensity among unemployed neighbours in the cluster) on the estimation sample.

Table 21: Repartition: Search through organisation intensity Mean vs. Max Endogenous

Mean / **Max**	0	0 to 0.5	0.5 to 1	1 to 1.5	1.5 to 2	2 to 2.5	2.5 to 3	NA	Total
0	5,484	0	0	0	0	0	0	0	5,484
1	0	3469	5125	0	0	0	0	0	8,594
2	0	220	2,942	1,718	1,721	0	0	0	6,601
3	0	0	162	313	230	86	151	0	942
NA	0	0	0	0	0	0	0	7,724	7,724
Total	5,484	3,689	8,229	2,031	1,951	86	151	7,724	29,345

* Table 21 gives the distribution of observations in categories of the job search through organisations endogenous variable in mean (average search intensity of unemployed neighbours in a cluster) versus the distribution of observations of the job search through organisations endogenous variable in maximum (maximum search insity among unemployed neighbours in the cluster) on the estimation sample.

Table 22: Distribution of endogenous variables: Mean vs. Max

Endogenous variables	Min	Q1	Median	Mean	Q3	Max	SD	NA
Av. search intensity								
Total	0	3	4	4.05	5	15	1.84	7,724
Network	0	0.5	1	1.3	2	4	0.97	7,724
Active and Direct	0	1.1	2	1.9	2.6	6	0.95	7,724
Organisations	0	0	0.8	0.8	1	3	0.63	7,724
Max. search intensity								
Total	0	4	5	5	7	15	2.2	7,724
Network	0	1	2	1.8	3	4	1.2	7,724
Active and Direct	0	2	3	2.5	3	6	1.14	7,724
Organisations	0	0	1	1.1	2	3	0.8	7,724
Estimation sample	29,345 obs. & 2,645 sectors & 7,899 clusters							

* Av. search intensity refers to the average search intensity of unemployed neighbours in a cluster. It corresponds to the endogenous effect in Manski's terminology. In this table, the endogenous effect is presented for each of the job search channels. Max. search intensity refers to the maximum/top search intensity among unemployed neighbours of the cluster. Total refers to the total search intensity of individuals. Network to the search intensity linked to the use of networks and Active and direct to direct and active actions leading to re-employment. Organisations to the search intensity linked to employment organisations.