Social capital and wages:
an econometric evaluation
of social networking's effects

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Abstract

The goal of this article is to get an econometric evaluation of the effects of the social network's mobilization, as a job search strategy, on wages. We make use of switching regression models to deal simultaneously with an endogenous selection issue in the network's choice and the existence of two different regimes of wage determination. Econometric estimates provide evidence for the existence of a selection effect on the choice of network but after correcting the selection bias on the wage equations, the effect of social network on wages is negative.

Keywords: Social capital, strong and weak ties, wages equations, selectivity bias, TDE-MLT longitudinal survey, switching model.

JEL Classification: **C**30, **J**31, **Z**13

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Introduction

Economic history is full of episodes in which the social structure has an impact on economic issues (see Coleman, 1984). Famous examples are the Asian rotating credit associations or the Mississippi bubble which happened in the beginning of the 18th century. Social structure embodies concepts such as the number of connections you have with other people and the trust you put in these people. First empirical studies on networks' effects have focussed on the relationship between individual behavior and the social network in which the individual belongs to. For example, Lee (1969) studies how women, who try to abort (which was illegal at this time), get information on physicians. Because physicians cannot promote for such practices, women have to use their own relation network to find a physician. Lee makes use of face-to-face interviews with women and physicians. The author presents the number of encounters of each women within her network and the type of contacts (mainly with feminine friends inside the same age class).

In labor markets, it is likely that all the information available, including those coming from relatives and friends sources, influences the probability of job return and the characteristics of that job, especially the wage. Granovetter (1973) has pointed out that *social network* (relatives, friends and workmates) has an impact on job transitions. Coleman (1990) has even identified this social network as a resource, which is now labelled *social capital*. Like human capital, social capital is a resource that any individual can use during his job search period. Although this idea has been widely developed in the sociologic literature, there is few economic studies on the effect of social networks on job transitions. Scarce economic analysis have focussed on theoretical effects of the network, within matching models (Montgomery, 1991; Mortensen and Vishwanath, 1994; Cahuc and Fontaine, 2002). According to these theoretical models, the use of social network (social networking) leads to faster and better transitions from unemployment to work.

On the basis of this existing framework, we develop a simple model which brings out the main effects of networking on wages. In addition, we propose an econometric evaluation of these effects. To fulfill that goal, the main methodological issue we have to take into account is a selection problem: it is likely that the selection rule for the use of social network resources, as a job search strategy, is endogenous. To deal with this problem, we will make use of a *switching regression model* which allows us to estimate in a one step procedure the selection equation and the wages equations, for the two regimes (using or not the network). This provides us efficient estimations for the three equations.

Our econometric study is based on the French longitudinal survey "*Trajectoires des Demandeurs d'Emploi et Marchés Locaux du Travail*" (TDE-MLT) from *Direction de l'Animation et de la Recherche, des Études et des Statistiques* (DARES). This survey informs us about individual attributes of 8125 persons who get unemployed for the first time during the second quarter of 1995. From that date, monthly report of individual situations (job seeker, employed, school attendance, . . .) is provided, over a 38 months duration.

This article is organized as follows: first part presents previous analysis on social networking literature and presents results related to job transition. Second part describes the data set and the econometric strategy. Third part comments results and last part concludes.

1 Networks and wages

In labor economics, the relation between the social environment (size and composition of the network) and job market issues is pretty intuitive. The pioneer work from Granovetter (1973) analyzes how people get information on vacant jobs. He recalls the different job search strategies as follows:

- Personal contacts, including relatives (**strong ties**) and workmates (**weak ties**). The strength of social relations depends on five criteria: the length of the relationship, the emotional intensity, the level of closeness, and the number of mutual favors done by members and the relation multiplicity (that is the exchanges plurality).

- Formal channels: job announces, hiring offices (public or private).

- Direct contacts with employers (postal or face-to-face).

Granovetter's objective is to contrast the effect of personal contacts (network: relatives, friends and workmates) and other search strategies on job return. Based on a sample of 266 individuals, his results provide support for the efficiency of the network. He also provides evidences on the dominance of weak ties on strong ties (for both transition and wages). This second result is related to the shorter length of the relation chain between work demand and supply when you use your network.

Other studies aim to link job search strategies and social networking (see Powell and Smith-Doerr, 1994). On the theoretical side, the emphasis is on the capacity, for the social network, to match labor supply and labor demand. On the demand side, it is preferred to hire people from a network in which other individual had previous successful experiences for similar jobs. Network's members behave as recruiting agents for the employer and engage their own credibility: this refers to the concept of *community governance* described by Bowles and Gintis (2002). This concept can be moved closer to this of *peer-pressure* (Kandel and Lazear, 1992). Employers anticipate that workers hired through networking are monitored by workers in place and then display a higher productivity. Consequently, they will propose them higher wages. On the supply side, networking speeds up information exchange and screens available job opportunities. Finally, networking is mostly an information transmission mechanism, between people with similar characteristics (social, religious or ethnical).

According to preceding studies, empirical studies lead to the following conclusions:

- The efficiency of networking in terms of job return. But, most of time, as pointed out by Campbell *et alii* (1986), people do not belong to the same networks.

- The influence of networking on the quality of job is mainly measured by the wage. This result, first pointed out by Granovetter (1974), is somewhat contrasted by Montgomery (1992). Montgomery shows that even if networking has a positive impact on job return, when weak ties are used, this does not imply necessarily higher wages. In addition, according to Lin (1982), it is likely that the distribution of available wages is not the same when you use the network and when you do not. In that case, it is important to distinguish between an information effect which gives you access to a large set of job opportunities and

a membership effect which gives you a better job only because of the network you belong to.

- The existence of determinants of the use and the composition of social networks. Burt (1990) shows that low-educated people have narrow networks, with strong ties. In contrast, individuals within high-educated social classes have large networks with weak ties.

These first results have led to additional investigations. Johnson *et alii* (1996) and Reingold (1999) focus on specific populations and analyze precisely the composition of the network: they study the effect of network's composition and not the fact to use or not the network. For American poor populations, Reingold establishes that hispanic newly settled individuals have better integration on job market that black people who settled in the U.S several generations before. In this study, it is outlined how important it is to take the composition and the size of the network into account. Using the multinomial regression model, Reingold proves that there are differences in the composition of networks, according to ethnical membership. In addition, these differences have an impact on job transitions when the networks are used to find a job.

More recently, many researchers have tried to redefine the concept of social capital and social networking (see Durlauf, 2002). Actually, there is no consensus on this issue and, as mentioned by Durlauf, the different underlying theories do not seem to oppose themselves.

Another way to extend that research topic is to consider macroeconomic job search models which take the social network into account (Pissarides, 1990). Using this approach, Montgomery (1991) develops an equilibrium job search model with an heterogeneity of productivity among job seekers. This model states that, for both sides (labor demand and labor supply), networking has positive impacts on job return, wages and also the profit of the company. But, in this study, social network is pretty large and do not distinguish (as in Granovetter) between weak and strong ties. The study from Mortensen and Visvanath (1994) considers only one type of job seeker and the heterogeneity lies in the distribution of wages, conditionally on the use of social network. Predictions of this model are similar with those from Montgomery: the quality of the job founded is higher when you use the social network, for wages and stability of jobs.

It is worthwhile to sum up most of the theoretical effects mentioned above in a basic framework (see figure 1). In this framework, we consider first that the job search environment is stationary, *i.e* job seekers use the same search strategies (methods and intensity) over time and have a constant reservation wage. Second, we suppose that individuals are homogenous, which means that labor supply is the same for all individuals. The only difference among individuals is the use of network, in addition to any other media (whatever the type of network).

Networking can create two effects on labor demand (L^D), which implies that job seekers do not face the same labor demand, depending on the choice of networking.

- First, when people use networks, they have access to a larger set of job opportunities. For a given real wage ($\frac{w}{p}$), network users receive more job offers (face a larger labor demand). This effect, denoted as an information effect ($\Delta I > 0$,

4

figure 1) shifts the labor demand for network users (L_N^D) to the right of the the labor demand for non-users ($L_{\overline{N}}^D$).

- Second, when people get a job through network, employers anticipate a higher productivity (*peer pressure* mechanism). Then for a given amount of job offers (L^D), network users get an higher wage. This productivity effect ($\Delta Y > 0$) shifts the labor demand in the same direction than the information effect.

As a result, equilibrium shifts from $E_{\overline{N}}$ to E_N (figure 1) and the equilibrium wage for network users ($(\frac{w}{p})_N^*$) is higher than for non-users ($(\frac{w}{p})_{\overline{N}}^*$).
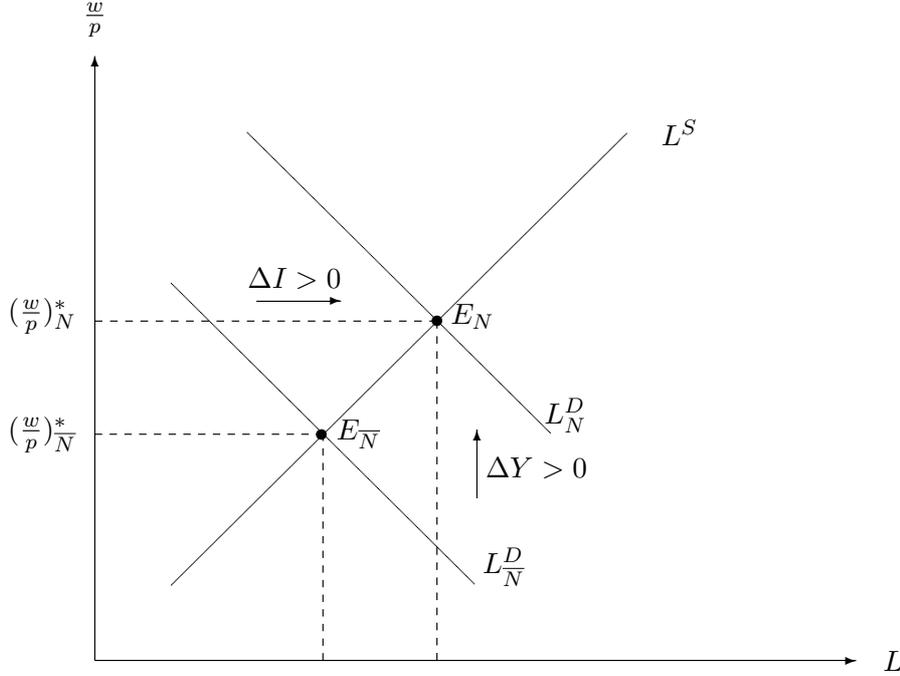

Figure 1: Networking and wages

On the empirical side, we have to outline that, to our knowledge, there is few studies which take the endogeneity problem of the choice for social networking into account. Notable exception is provided by Margolis and Simmonet (2003). As mentioned by many authors, this problem is likely to create bias when estimating wage equations. Following Glaeser, Laibson and Sacerdote (2002), networking, which is part of social capital, can be viewed as an individual optimization behavior related on individual attributes. Then, it seems more relevant to estimate wage equations conditionally on the networking choice. This is why we make us of the *switching regression model* in this paper.

2 Econometric issue: the network's effects on wages

2.1 Data: the TDE-MLT survey

Our econometric analysis is based on French data from the "Trajectoires des Demandeurs d'Emploi – Marchés Locaux du Travail" (TDE-MLT) survey, conducted by DARES. This longitudinal survey retraces all the transitions on labor market experienced, during 38 months, by unemployed people registered in the public employment agency (ANPE) between April and June 1995. The 8125 interviewed individuals live in eight particular areas located in the South of France ("PACA" area), the North of France ("Nord" area) or in the suburbs of Paris ("Ile-de-France" area). For each of them, the TDE-MLT survey informs on personal attributes (see list of available variables in appendix 1). It also details the conditions of their first job access observed after the ANPE registration in 1995. We focus our analysis on this particular transition which lasts ten months in average. During this period, 33.5% of the unemployed people mobilize their social networks to find a job. Two precise details must here be provided about the definition of networks in the TDE-MLT survey. First, networks are defined as the use of relatives, friends or associations *i.e.* strong ties. But, they do not include professional links, *i.e.* weak ties, not informed in this survey. Second, only 3% of the interviewed people use networks as a sole search media. Well, among the 33.5% of people using networks, a large part of them combines networks with an other channel (direct applications, advertisement, public or private employment agencies).

During the observed period, about 80% of the unemployed people find a job. We focus attention on the successful transitions and in particular on the obtained wages. As a large part of people (35,7%) find part-time jobs, we prefer to perform our analysis on the hourly wages than on monthly wages (4280 observations). Besides, as some variables are not perfectly informed, we use a sample of 2510 observations[1]. In this working sample, the average hourly wage is about FR 37.4 (5.70 euros) that is very close from the minimal wage (FR 36.98=5.64 euros).

Table 1: Hourly wage and networks

	Mean	S.D.
Networks user	37.97	17.33
Networks non-user	37.07	17.28
Total	37.37	17.30

S.D. : Standard deviation

According to table 1, we can note that, in our sample, persons who use networks receive higher hourly wages, on average. This advantage is relatively small (FR 0.90), smaller than those highlighted in sociological studies (Granovetter, 1973).

Descriptive statistics (table 2) also underline differences in average characteristics of users and non-users of social relations.

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[1] Statistical analysis shows no significant differences between our working sample and the full sample of people leaving unemployment in terms of average individual attributes, firm characteristics, hourly wages and network's choice.

Table 2: Individual attributes and network's use (in %)

	Users of networks	Non-users of networks	Total
MALE : gender=male	54.3	51.5	52.4
EDUC1 : inferior to "brevet" diploma	22.9	22.3	22.5
EDUC2 : CAP or BEP diploma	36.5	44.4	41.8
EDUC3 : A-level	16.8	18.4	17.8
EDUC4 : University	23.7	14.9	17.8
EXP : having a professional experience	84.5	83.0	83.5
PERINT : father's occupation=executive	17.7	13.4	14.9
MERINT : mother's occupation=executive	8.9	5.6	6.7

As in sociological studies, statistical results show us that network's users are more graduated (notably for the university degree) and more skilled. Besides, they belong more to upper-class families. These results claim then for a more extensive analysis of the individual choice process which seems to underly the networks use. However, we must stressed out that these individual attributes are suspected to influence not only the networks choice but also hourly wages (Mincer, 1958). Finally, neglecting the potential endogeneity of network's use can bias the estimated effect of networks on wages. In order to overcome this difficulty, we then propose to use a econometric method allowing to take the selection rule of networks into account.

2.2 Methodology

To estimate the network's effect on wages, several estimation methods are available. The easiest method consists in estimating a Mincer's equation (OLS regression) including among explanatory factors a dummy variable which is equal to one when the unemployed people use networks to search a job. We then have:

$$\log(w_i) = \beta_0 + \alpha NETW_i + \beta_1' X_i + \varepsilon_i \tag{1}$$

where w_i denotes hourly wage of an individual i, $NETW_i = 1$ if networks are used, X_i is a vector of individual wage explanatory factors and ε_i the error term. This allows us to control for (observed) heterogeneity among job seekers in order to get close to assumptions of figure 1.

In this equation, α is the difference in constant absolute value for wage (in logarithm) for network's users rather than network's non-users.

Alternatively, we can estimate an OLS wage regression omitting the constant term but including both two dummies: the first one is equal to one when networks are used and the second is equal to one if networks are not used.

$$\log(w_i) = \alpha_1 NETW_i + \alpha_2 NNETW_i + \beta_1' X_i + \varepsilon_i \tag{2}$$

where $NNETW_i = 1$ if networks are not used to search a job.

In this case, testing for equality between α_1 and α_2 informs us whether network's choice influence wages or not.

However, these two equivalent methods suffer from a major difficulty: both consider networks choice as exogenous. On the contrary, statistical analysis of our data set (see above) leads us to strongly suspect that network's use is selective. We must

then mobilize econometric methods allowing to correct this endogeneity.

To fulfill this goal, instrumental methods, such as the one from Heckman and Robb (1985), can be used. Based on a two-step method, this method allows to first estimate the probability of using networks and then to analyze the determinants of hourly wages, introducing as explanatory variable the estimated probability of using networks (instead of the dummy).
We then have:

$$\log(w_i) = \beta_0 + \alpha PNETW_i + \beta_1' X_i + \varepsilon_i \qquad (3)$$

where $PNETW$ is the estimated probability of using networks, calculated from the estimation of the following choice equation (probit estimation):

$$NETW_i = \gamma' Z_i + \mu_i \qquad (4)$$

where Z_i is a vector of explanatory factors of networks choice.
According to this instrumentation and after the correction of the variance-covariance matrix[2], an unbiased estimation of networks effect on wages can be obtained.

However, endogenous switching models (Lee, 1978; Maddala, 1986) seems to be an interesting alternative method to estimate the network's effect on wages. Indeed, this method allows to jointly estimate the network's choice and two wage equations, depending on whether networks are mobilized or not. Compared to the instrumental method, the switching technique gets better results in two ways. First, it allows to test the network's impact both on wages and on explanatory factors of wages, as recommended by Lee (1982). Second, it is based on full information maximum likelihood technique and then provide directly, without additional correction, the network's effect on wages.

Now, let us detail the switching model structure. We define two states: state 1 and state 0, corresponding respectively to using or not social networks as search channel. Let w_1 and w_0 be the hourly wages received in the first job found after 1995, according to the state. Corresponding wage equations can then be written as follows:

$$\log(w_{1i}) = \beta_1' X_i + \varepsilon_{1i} \qquad (5)$$

$$\log(w_{0i}) = \beta_0' X_i + \varepsilon_{0i} \qquad (6)$$

where X_i is a vector of explanatory variables (individuals attributes, proxies of expected productivity, and job characteristics), ε_1 et ε_0 are error terms, supposed to be distributed as a normal function with null mean and respective variances σ_1^2 and σ_0^2.
However, network's choice is not exogenous: it depends on differences between net gains associated to each alternative (using networks or not). Let us note $NETW^*$, the net gain of using networks. An individual i, searchs his job through networks if:

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[2]Two-step econometric methods can lead to an under-estimation of standard errors and then can bias evaluation of the coefficients significance level. A correction of the variance-covariance matrix is then necessary (Murphy and Toppel, 1985).

$$NETW_i^* = \gamma'Z_i + \mu_i > 0 \qquad (7)$$

where Z_i is a vector of explanatory factors of networks choice (individual attributes, job search characteristics, father and mother's job occupation) and μ an error term distributed as a normal function with null mean and a variance normalized to one in order to allow for the estimation of the coefficients.

But $NETW_i^*$ is a latent variable which can not be observed. We observe only the fact that unemployed people really use or not networks. We then have:

$$\begin{cases} NETW_i = 1 & \text{if} \qquad NETW_i^* > 0 \\ NETW_i = 0 & \text{if not.} \end{cases}$$

Finally, we observe :

$$\begin{cases} y_i = \log(w_{1i}) & \text{if} \quad NETW_i = 1 \\ y_i = \log(w_{0i}) & \text{if} \quad NETW_i = 0 \end{cases}$$

with:

$$\Sigma \quad = \quad \begin{pmatrix} \sigma_1^2 & \rho_{10} & \rho_{1\mu} \\ \rho_{10} & \sigma_0^2 & \rho_{0\mu} \\ \rho_{1\mu} & \rho_{0\mu} & 1 \end{pmatrix}$$

So, switching models allow to estimate wages conditionally to the network's mobilization. Besides, the variance-covariance matrix Σ can be estimated in one step. Finally, we have endogenous switching models if $\rho_{1\mu}$ et $\rho_{0\mu}$ are significantly different from zero, that is if errors of the wage equations and errors of the choice equation are correlated.

Switching models are then based on the analysis of three variables but each of them is partly observed (Maddala, 1983). The selection variable, $NETW_i^*$, is not directly observed but only through a dummy $NETW_i$. Besides, w_{1i} is observed only if $NETW_i = 1$ and w_{0i} only if $NETW_i = 0$. Switching models can be estimated without identification problems, except for ρ_{10}, because the two states can not be observed simultaneously. As wages are observed conditionally to networks use, it is more interesting to analyze conditional wage distributions (Poirier and Rudd, 1981). The expected wage, conditionally to network's choice, can be calculated as follows:

$$\begin{aligned} E[\log(w_{1i})|NETW_i = 1] &= \beta_1'X_i + E[\varepsilon_{1i}|\mu_i > -\gamma'Z_i] \\ &= \beta_1'X_i + \sigma_1\rho_{1\mu}\frac{\phi(\gamma'Z_i)}{\Phi(\gamma'Z_i)} \qquad (8) \end{aligned}$$

In the same way, the expected wage, conditionally of the non-use of networks, is given by:

$$E[\log(w_{0i})|NETW_i = 0] = \beta_0' X_i + \sigma_0 \rho_{0\mu} \frac{-\phi(\gamma' Z_i)}{1 - \Phi(\gamma' Z_i)} \qquad (9)$$

Switching models estimation requires maximum likelihood computation. Now, the log likelihood function associated to our model is composed of two parts and is written as :

$$
\begin{aligned}
\log L \;=\; & \sum_{i=1}^{n} prob(NETW_i = 1) f(\log(w_{1i})|NETW_i = 1) \\
& + prob(NETW_i = 0) f(\log(w_{0i})|NETW_i = 0) \qquad (10)
\end{aligned}
$$

with :

$$
\begin{aligned}
prob(NETW_i = 1) \;=\;& \Phi(\gamma' Z_i) \\
prob(NETW_i = 0) \;=\;& 1 - \Phi(\gamma' Z_i) \\
f(\log(w_{1i})|NETW_i = 1) \;=\;& [\Phi(\gamma' Z_i)]^{-1} \sigma_1^{-1} \phi(\sigma_1^{-1}(\log(w_{1i}) - \beta_1' X_{1i})) \times \\
& \Phi\{(1 - \frac{\rho_{1\mu}^2}{\sigma_1^2})^{-\frac{1}{2}} [\gamma' Z_i - \frac{\rho_{1\mu}}{\sigma_1^2}(\log(w_{1i}) - \beta_1' X_{1i})]\} (11) \\
f(\log(w_{0i})|NETW_i = 0) \;=\;& [1 - \Phi(\gamma' Z_i)]^{-1} \sigma_0^{-1} \phi(\sigma_0^{-1}(\log(w_{0i}) - \beta_0' X_{0i})) \times \\
& \Phi\{(1 - \frac{\rho_{0\mu}^2}{\sigma_0^2})^{-\frac{1}{2}} [\gamma' Z_i - \frac{\rho_{0\mu}}{\sigma_0^2}(\log(w_{0i}) - \beta_0' X_{0i})]\} (12)
\end{aligned}
$$

The maximization of this function allows us to estimate the following parameters:
- γ: coefficients of the factors explaining network's choice.
- β_1: coefficients of the factors explaining wages, conditionally of network's use.
- β_0: coefficients of the factors explaining wages, conditionally of the non-mobilization of networks.
- $\rho_{1\mu}$ and $\rho_{0\mu}$: correlation terms between the network's choice equation and the wage equations.
- σ_1^2 and σ_0^2: wage variances in the two states.

2.3 Econometric results and comments

Before commenting econometric results of the switching regression (tables 4 and 5), let us discuss about the robustness of the switching specification.

For that, we compare results of the four alternative methods available (and detailed above) to test whether searching through networks influence wages (see results for OLS regression and Heckman and Robb's method in appendix 2 and 3). First, the two OLS wage equations (see equations 1 and 2) both conclude to a non-significant impact of network's choice on wages. This result seems to indicate that networks are not efficient in terms of wages. But, it can be biased by the non-correction of the potential endogeneity of network's choice. Instrumental methods (see equation 3) seem then to be more correct. But, this estimation[3] also concludes that networks produce no effect on wages, even if network's choice depends on several individual characteristics (see equation 4).

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[3]This result is obtained without correcting the covariance matrix and by supposing that wages explanatory factors are similar for network's users and non-users.

Allowing both to test the network's choice endogeneity and whether wage explanatory factors are different according to networks choice and then adopting a less restrictive method, switching regression gives two interesting results.

First, we can note that correlation coefficients between selection equation (networks choice) and wages equations ($\rho_{1\mu}$ and $\rho_{0\mu}$) are significantly different from zero. This result indicates that the network's choice is endogenous (see table 5 for more details). Then, switching models are more adapted than simple OLS wage regressions imposing automatically the exogeneity of network's choice. More precisely and according to formulas of expected wages conditionally to the network's use (see equations 8 and 9) and to the sign of correlation terms ($\rho_{0\mu}$ and $\rho_{1\mu}$) neglecting selection would then overestimate wages both for users and non-users of social networks. But, this overestimation would be larger for users.

Second, switching regression seems also to be a best specification than instrumental methods, such as this of Heckman and Robb (1985). As it is detailed *infra*, switching regression highlights that explanatory factors of hourly wages differs strongly whether networks are used or not. Well, the Heckman and Robb's method does not allow to test such a possibility and then impose a restriction which can influence results.

As switching regression seems to be the best specification among those available, let us focus on the results given by this model. First, let us compare observed and predicted wages (see table 3).

	Networks users		Networks non-users	
	Observed wages	Predicted wages	Observed wages	Predicted wages
Mean	37.97	36.45	37.07	39.10
S.D.	17.33	8.33	17.28	8.13

S.D: Standard deviation

Predictions for wages from the switching model

Table 3: Observed and predicted wages

As underlined in the beginning of this section, we observe a small difference in hourly wages in favor of network's users. But, the endogeneity bias correction allowed by switching regression leads to an opposite result: estimated wages are more than 7% (that is FR 2.65 additional) higher for non-users. Switching regression then gives stronger results about network's efficiency than OLS or instrumental methods: we do not conclude that searching a job through networks do not affect hourly wages but significantly and negatively influence them.

Network's efficiency seems then to be only apparent because of selection bias (see *infra*). Indeed, as networks are more used by graduated and skilled people and because these attributes are positively linked with wages, hourly wages of networks users are artificially higher. After controlling for selection bias, we obtain the real effect of networks which is negative. This result moderates predictions of equilibrium job search models (Montgomery, 1991; Mortensen and Vishwanath, 1994; Cahuc and Fontaine, 2002) which conclude to a strong positive effect of networks on wages, supposing that networks choice is exogenous and adopting a large definition of networks. However, it must be reminded that we observe only strong ties and our results can

be applied only on these particular links. Our result seems even to be in the line of sociological studies (Granovetter, 1973) about "the weakness of strong ties" compared to "the strength of weak ties" (see section 1). But, this needs further empirical investigations.

As noted in the general discussion, microeconometric results from the switching regression highlight that individual attributes significantly influence the networks choice. For example, males have a higher probability to search a job through social relations. Besides, French people with French parents have higher probabilities to use social networks. Unlike gender and nationality, marital status seems to have no impact on networks choice. On the contrary, age has a positive influence on the probability of choosing networks. Indeed, older people may have had more opportunities to build social links and then may have larger networks. But, this seems not to be caused by professional experience: EXP variable has a negative effect on networks choice probability. This result could be explained by the fact that experience encourages weak links development rather than (and maybe to the detriment of) strong links. In the opposite and in the line of sociological studies (Granovetter, 1973), the educational level (EDUC1 to EDUC3, by contrast to EDUC4) increases the probability of searching through networks. Indeed, diploma levels act positively both on links density and quality, making potentially easier and more profitable networks mobilization.

In addition to individual attributes, contextual factors of the search period explain the network's choice. Leaving unemployment faster (in 1995 -DATE1- or in 1996 -DATE2- than later -DATE3) increases the probability of searching through social strong ties. This result can be commented in two ways. First, it could reflect the relatively good macroeconomic situation in France in 1995, compared to following years. People were facing less difficulties to find a job which may favor networking. Second, this impact could also indicate that network's mobilization appears in the beginning of the unemployment period. This would underline that network's choice depends on time and then is non-stationary. Unfortunately, this non-stationary hypothesis could not be tested here, because TDE-MLT survey informs only on search media used during the whole job search period and does not indicate the temporal process of choices. However, we can note that receiving unemployment benefits (ALLOC), which is considered as a main source of non-stationarity in the job search theory, increases the probability of using networks. This can lead us to prefer the hypothesis of non-stationarity in network's choice, without concluding definitively about this fact.

Spatial constraints also influence the network's choice probability. Indeed, this probability is smaller when people can go easily to a public employment agency (ANPFAC). In the same line, local areas have strong impacts on network's mobilization. Using South local areas (Aix-en-Provence, Marseille, Etang-de-Berre) as references, econometric results show that leaving in the North of France or near Paris decreases the probability of searching through social relations. But, this probability is not affected by the fact of having any transportation facility (MTRANS).

Finally, the job occupation of parents also influence the network's choice. Unemployed people whose parents are executive have a higher probability of using networks. Because of network's transitivity, these individuals can mobilize their parents' relations in order to find a job. As noted by sociological studies, parents could then be considered as a relational bridge between their children and their social relations.

Switching regression then concludes that the network's choice is selective. But, this also highlights a strong heterogeneity in explanatory factors of hourly wages, according to the networks use or not (see table 5). Indeed, for network's non-users, we find usual factors of wages. Results confirm the expected and positive impact of diploma (EDUC1, EDUC2), which remains an indicator of future individual productivity. But, this argument seems not to be valid for professional experience (EXP) which have no significant influence on wages. This surprising result could be explained by the fact that EXP variable just indicates whether people have had job experience or not. But, it does not inform on the experience duration. Previous jobs could be short-term jobs, less easily valorized when wages are negociated in the hiring process. Econometric results also show that the actual job quality increases wages. Long-term jobs (CDI) or high-skilled jobs are associated with higher wages. However, one result is a bit surprising: the impact of unemployment benefits (ALLOC). These benefits do not affect wages (for non-users and users), although the job search theory indicates that benefits increase reservation wages and then wages. This contradictory result could be caused by the fact that ALLOC variable only describes whether people receive or not unemployment compensations and does not indicate the amount received. We can also note that the unemployment duration and then the year at which people leave unemployment (DATE1, DATE2) have no impact on wages for all individuals (users and non-users). Nevertheless, the wage equation estimation for networks non-users gives globally the expected results.

This is not the case for the estimation for networks users. For them, only firm and job characteristics explain hourly wages. Individual attributes have no impact, excepting gender. This result could follow from the fact that networks are used in majority by graduated and skilled people. After controlling for the influence of education level and experience on network's choice, these factors have no longer impact on wages, because network's users are almost homogenous in terms of these two attributes. For this sub-sample, heterogeneity in hourly wages can then be attributed to variability in jobs characteristics, such as contract duration, job skill level, firm size, each of them having a positive effect on wages.

Table 4: Switching regression (Part 1)

Equation 1 : the network's choice		
Explanatory factors	Coefficient	Student t
Constant	−1.834	−17.374***
MALE: gender=male	0.524	4.078***
LAGE: age in logarithm	0.636	24.487***
SINGL: being single	0.023	1.575^{ns}
NAT1: French nationality and French parents	ref	
NAT2: French nationality and European (non French) parents	−0.872	−4.310***
NAT3: French nationality and non European parents	−0,117	−5.131***
NAT4: Non-French nationality and European (non French) parents	−0.315	−4.938***
NAT5: Non-French nationality and non European parents	−0.096	−3.365***
Educational level		
EDUC1: inferior or equal to "brevet" diploma	−0.299	−11.001***
EDUC2: between "brevet" and vocational training certificate	−0.409	−17.320***
EDUC3: equal to A-level	−0.239	−8.921***
EDUC4: university	ref	
EXP: having a previous professional experience	−0.157	−7.516***
Job search context		
ALLOC: having received unemployment benefits	0.121	7.621***
DATE1: leaving unemployment in 1995	0.058	3.150***
DATE2: leaving unemployment in 1996	0.198	11.689***
DATE3: leaving unemployment in 1997	ref	
MTRANS: having any transportation facility	0.122	0.836^{ns}
ANPFAC: easy access to a public employment agency	−0.071	−5.571***
Geographical area		
Mantes la Jolie	−0.148	−5.853***
Cergy-Pontoise	−0.408	−19.680***
Poissy-Les Mureaux	−0.193	−8.547***
Lens	−0.598	−27.787***
Roubaix	−0.805	−41.251***
Aix en Provence, Étang de Berre, Marseille	ref	
Parents' job occupation		
PEROUV: blue-collar father	−0.114	−4.397***
PEROUVQ: skilled blue-collar father	−0.077	−3.861***
PEREMPL: employee father	−0.144	−5.596***
PERAGR: farmer father	−0.205	−8.106***
PERINT: executive father	ref	
MEROUV: blue-collar mother	−0.125	−6.321***
MEROUVQ: skilled blue-collar mother	−0.059	$−1.260^{ns}$
MEREMPL: employee mother	−0.148	−7.765***
MERAGR: farmer mother	−0.127	−4.468***
MERINAC: housewife	−0.093	−5.877***
MERINT: executive mother	ref	

Data source: TDE-MLT survey, DARES

*** : significant at 1%. ** : significant at 5%. * : significant at 10%.

Table 5: Switching regression (part 2)

| | Equation 2 : wage equation for network's non-users | | Equation 3 : wage equation for network's users | |
| | Explained variable : hourly wages (in logarithm) | | | |
Explanatory factors	Coefficient	Student t	Coefficient	Student t
Constant	4.254	23.555^{***}	3.908	32.948^{***}
MALE: gender=male	−0.016	$−0.698^{ns}$	0.027	1.683^{*}
LAGE: age in logarithms	−0.017	$−0.373^{ns}$	−0.033	$−1.031^{ns}$
Educational level				
EDUC1: inferior or equal to "brevet" diploma	−0.115	$−3.260^{**}$	0.013	0.476^{ns}
EDUC2: between "brevet" and vocational training certificate	−0.062	$−1.946^{*}$	0.007	0.274^{ns}
EDUC3: equal to A-level	−0.019	$−0.498^{ns}$	0.029	1.022^{ns}
EDUC4: university	ref		ref	
EXP: having a professional experience	−0.049	$−1.239^{ns}$	0.031	1.270^{ns}
ALLOC: receiving unemployment benefits	−0.042	$−1.512^{***}$	0.007	0.346^{ns}
DATE1: leaving unemployment in 1995	0.017	0.555^{ns}	−0.010	$−0.456^{ns}$
DATE2: leaving unemployment in 1996	−0.019	$−0.0597^{ns}$	0,023	1.074^{ns}
DATE3: leaving unemployment after 1997	ref		ref	
Job and firm characteristics				
AIDE: having a granted job	−0.110	$−3.687^{***}$	−0.024	$−1.193^{ns}$
CDD: having a non-permanent job	−0.054	$−1.728^{*}$	0.014	0.656^{ns}
INTERIM: having a temporary job	−0.079	$−2.149^{**}$	−0.067	$−2.845^{***}$
CDI: having a permanent job	ref		ref	
PME: working in a small firm	−0.023	$−0.985^{ns}$	−0.052	$−3.240^{***}$
OUVR: being blue-collar	−0.435	$−11.743^{***}$	−0.440	$−17.774^{***}$
OUVRQ: being skilled blue-collar	−0.330	$−8.853^{***}$	−0.327	$−13.491^{***}$
EMPLOY: being employee	−0.487	$−18.552^{***}$	−0.379	$−20.742^{***}$
PRINTER: being executive	ref		ref	
SECTEUR1: working in agricultural sector	ref		ref	
SECTEUR2: working in industrial sector	−0.053	$−1.036^{ns}$	0.078	1.748^{*}
SECTEUR3: working in service sector	−0.073	$−1.679^{*}$	0.027	0.789^{ns}
σ_j^2 $(j=0,1)$	0.312	87.954^{***}	0.313	38.304^{***}
$\rho_{j\mu}$ $(j=0,1)$	0.062	9.190^{***}	−0.237	$−1.864^{*}$

Log-likelihood: −20670.56. Number of observations: 2510

Data source: TDE-MLT survey, DARES

*** : significant at 1%. ** : significant at 5%. * : significant at 10%.

3   Conclusion

From a review of economic and sociologic literature, we propose, in this article, a simple model which sums up the effect of networking on wages (figure 1). Two positive effects are expected. First, for a given real wage, the network's use would give access to job offers (information effect). Second, for a given amount of offers, networking would ensure a higher wage (productivity effect). Finally, networking leads to a higher equilibrium wage. Our objective is to test this prediction.

In order to have an unbiased estimation of network's impact, an original method is here chosen: the switching regression. This method allows us to deal with selection bias in network's choice and to test whether wages explanatory factors are identical for network's users and non-users. Based on the TDE-MLT French survey, the switching regression leads us to conclude that the network's choice is endogenous. But, after controlling for this selectivity bias, networking produces a negative impact on hourly wages. Our study seems then to reject that networks are always associated with higher wages. It contracts with the expected effects given by figure 1. This apparent contradiction could be explained by three facts. First, the hypothesis of stationary environment is too restrictive. Job seekers could have changed their search strategy during the considered period. Second, networks' users can have unobserved attributes, negatively correlated with wages. Third, networking is really inefficient in terms of wages (no information or productivity effects). This last comment can be moderate by the fact that we here can only test the effect of strong ties and yet their effectiveness is not proved. Our results seem then to be more in the line of sociological results which highlight the weakness of strong links.

In addition, it is worthwhile to contrast our econometric results with those of Margolis and Simonnet (2003). Using a French longitudinal survey, they find a positive effect of the network on wages. One reason which may explain this difference is their definition of network. While we observe only the use of strong ties, they have a broader definition of network which embodies strong and weak ties.

However, to strengthen these first interesting results, further investigations could must be done to precise the network's effect. An unemployment duration analysis should be an interesting further study in order to complete our study on wages. Indeed, we can wonder whether the ineffectiveness of networking in terms of wages could not be balanced by an effectiveness in terms of unemployment duration. Besides, in the estimation of the exit rates from unemployment, we can control for the unobserved heterogeneity of job seekers.

Table 6: Data description

Variable	Mean or Frequencies*
Individual attributes	
MALE: gender=male	0.52
AGE: age	31.13
SINGL: being single	40.2
NAT1: French nationality and French parents	0.72
NAT2: French nationality and European (non French) parents	0.12
NAT3: French nationality and non European parents	0.06
NAT4: Non French nationality and European (non French) parents	0.02
NAT5: Non French nationality and non European parents	0.06
Educational level and professional experience	
EDUC1: inferior or equal to "brevet" diploma	0.23
EDUC2: between "brevet" and vocational training certificate	0.42
EDUC3: equal to A-level	0.17
EDUC4: university	0.18
EXP: having a previous professional experience	0.84
Job search context	
NETW: searching through networks	0.34
NNETW: searching without networks	0.66
ALLOC: having received unemployment benefits	0.59
MTRANS: having any transportation facility	0.76
ANPFAC: having an easy access to public employment agencies	0.54
DATE1: leaving unemployment in 1995	0.55
DATE2: leaving unemployment in 1996	0.35
DATE3: leaving unemployment after 1997	0.10
Local area	
Mantes la Jolie	0.12
Cergy-Pontoise	0.15
Poissy-Les Mureaux	0.16
Lens	0.22
Roubaix	0.17
Aix en Provence, Étang de Berre, Marseille	0.18
Parents' job occupation	
PEROUV: father = blue-collar	0.18
PEROUVQ: father = skilled blue-collar	0.33
PEREMPL: father = employee	0.12
PERAGR: father = farmer	0.11
PERINT: father = executive	0.15
MEROUV: mother = blue-collar	0.10
MEROUVQ: mother = skilled blue-collar	0.02
MEREMPL: mother = employee	0.22
MERAGR: mother = farmer	0.05
MERINA: mother = housewife	0.52
MERINT: mother = executive	0.07

Data Source: TDE-MLT survey (DARES). *: Frequencies are given for discrete variables. **: EXP is a dummy variable for the for the existence of any previous job experience and does not describe the duration of this experience.

Table 7: Data description (continued)

Variable	Mean or Frequencies*
Job and firm characteristics	
WAGE: hourly wage (in FR)	36.91
PME: working in a small firm (less than 50 employees)	0.57
Type of job occupation	
OUVR: blue-collar	0.21
OUVRQ: skilled blue-collar	0.17
EMPLOYE: employee	0.43
PRINTER: executive	0.19
Type of job contract	
AIDE: having a granted job	0.32
CDD: having a non-permanent job	0.24
INTERIM: having a temporary job	0.18
CDI: having a permanent job	0.26
Firm activity sectors	
SECTOR1: working in agricultural sector	0.07
SECTOR2: working in industrial sector	0.08
SECTOR3: working in service sector	0.85

Data Source: TDE-MLT survey (DARES)

*: Frequencies are given for discrete variables

Table 8: OLS regression 1

Explanatory factors	Coefficient	Student t
Constant	-3.945	-43.607^{***}
MALE: gender=male	0.017	1.358^{ns}
LAGE: age in logarithm	-0.022	-0.857^{ns}
Educational level and experience		
EDUC1: inferior or equal to "brevet" diploma	-0.029	-1.414^{ns}
EDUC2: between "brevet" and vocational training certificate	-0.027	-1.479^{ns}
EDUC3: equal to A-level	-0.007	-0.324^{ns}
EDUC4: university	ref	
EXP: having a previous professional experience	0.053	2.541^{***}
Job search context		
ALLOC: having received unemployment benefits	-0.014	-0.969^{ns}
DATE1: leaving unemployment in 1995	0.008	0.467^{ns}
DATE2: leaving unemployment in 1996	0.012	0.683^{ns}
DATE3: leaving unemployment in 1997	ref	
Job and firm characteristics		
AIDE: having a granted job	-0.048	-2.898^{***}
CDD: having a non-permanent job	-0.007	-0.364^{ns}
INTERIM: having a temporary job	-0.063	-3.310^{***}
CDI: having a permanent job	ref	
PME: working in a small firm	-0.040	-3.155^{***}
OUVR: being blue-collar	-0.464	-22.979^{***}
OUVRQ: being skilled blue-collar	-0.341	-16.279^{***}
EMPLOY: being employee	-0.413	-23.636^{***}
PRINTER: being executive	ref	
SECTEUR1: working in agricultural sector	ref	
SECTEUR2: working in industrial sector	0.057	1.775^{*}
SECTEUR3: working in service sector	0.018	0.742^{ns}
NETW: searching through social networks	0.016	1.273^{ns}
$R^2 = 0.23$. Number of observations: 2510		

Data Source: TDE-MLT survey (DARES)

***: significant at 1%. **: significant at 5%. *: significant at 10%.

Table 9: OLS regression 2

Explanatory factors	Coefficient	Student t
MALE: gender=male	0.017	1.358^{ns}
LAGE: age in logarithm	-0.022	-0.857^{ns}
Educational level and experience		
EDUC1: inferior or equal to "brevet" diploma	-0.029	-1.414^{ns}
EDUC2: between "brevet" and vocational training certificate	-0.027	-1.479^{ns}
EDUC3: equal to A-level	-0.007	-0.324^{ns}
EDUC4: university	ref	
EXP: having a previous professional experience	0.053	2.541^{***}
Job search context		
ALLOC: having received unemployment benefits	-0.014	-0.969^{ns}
DATE1: leaving unemployment in 1995	0.008	0.467^{ns}
DATE2: leaving unemployment in 1996	0.012	0.683^{ns}
DATE3: leaving unemployment in 1997	ref	
Job and firm characteristics		
AIDE: having a granted job	-0.048	-2.898^{***}
CDD: having a non-permanent job	-0.007	-0.364^{ns}
INTERIM: having a temporary job	-0.063	-3.310^{***}
CDI: having a permanent job	ref	
PME: working in a small firm	-0.040	-3.155^{***}
OUVR: being blue-collar	-0.464	-22.979^{***}
OUVRQ: being skilled blue-collar	-0.341	-16.279^{***}
EMPLOY: being employee	-0.413	-23.636^{***}
PRINTER: being executive	ref	
SECTEUR1: working in agricultural sector	ref	
SECTEUR2: working in industrial sector	0.057	1.775^{*}
SECTEUR3: working in service sector	0.018	0.742^{ns}
NETW: searching through social networks	3.962	43.058^{***}
NNETW: searching without social networks	3.945	43.607^{***}
$R^2 = 0.23$. Number of observations: 2510		

Data Source: TDE-MLT survey (DARES)

***: significant at 1%. **: significant at 5%. *: significant at 10%.

Table 10: Heckman and Robb's method (Part 1)

Equation 1: the network's choice (probit estimation)		
Explanatory factors	Coefficient	Student t
Constant	−1.606	−3.602***
MALE: gender=male	0.084	1.498^{ns}
LAGE: age in logarithm	0.588	4.716***
SINGL: being single	0.045	0.660^{ns}
Nationality		
NAT1: French nationality and French parents	ref	
NAT2: French nationality and European (non French) parents	−0.075	−0.875^{ns}
NAT3: French nationality and non European parents	0.079	0.718^{ns}
NAT4: Non-French nationality and European (non French) parents	−0.209	−0.9532^{ns}
NAT5: Non-French nationality and non European parents	0.002	0.015^{ns}
Educational level		
EDUC1: inferior or equal to "brevet" diploma	−0.204	−2.297**
EDUC2: between "brevet" and vocational training certificate	−0.281	−3.509***
EDUC3: equal to A-level	−0.246	−2.711***
EDUC4: university	ref	
EXP: having a previous professional experience	−0.154	−1.673*
Job search context		
ALLOC: having received unemployment benefits	0.061	0.933^{ns}
DATE1: leaving unemployment in 1995	0.021	0.278^{ns}
DATE2: leaving unemployment in 1996	0.067	0.872^{ns}
DATE3: leaving unemployment in 1997	ref	
MTRANS: having any transportation facility	0.022	0.332^{ns}
ANPFAC: easy access to a public employment agency	−0.037	−0.666^{ns}
Geographical area		
Mantes la Jolie	−0.191	−1.892*
Cergy-Pontoise	−0.357	−3.770***
Poissy-Les Mureaux	−0.277	−2.992***
Lens	−0.408	−4.533***
Roubaix	−0.598	−6.184***
Aix en Provence, Étang de Berre, Marseille	ref	
Parents' job occupation		
PEROUV: blue-collar father	−0.326	−3.576***
PEROUVQ: skilled blue-collar father	−0.236	−3.076***
PEREMPL: employee father	−0.251	−2.582***
PERAGR: farmer father	−0.298	−2.841***
PERINT: executive father	ref	
MEROUV: blue-collar mother	−0.009	−0.071^{ns}
MEROUVQ: skilled blue-collar mother	0.158	0.805^{ns}
MEREMPL: employee mother	−0.107	−0.966^{ns}
MERAGR: farmer mother	−0.006	−0.039^{ns}
MERINAC: housewife	−0.083	−0.795***
MERINT: executive mother	ref	
Log-likelihood = −1454.62. Number of observations: 2510		

Data Source: TDE-MLT survey (DARES)

***: significant at 1%. **: significant at 5%. *: significant at 10%.

The estimated probability of using networks, PNETW, is computed from this probit estimation

Table 11: Heckman and Robb's method (Part 2)

Equation 2: wage OLS equation		
Explanatory factors	Coefficient	Student t
Constant	3.963	41.817***
MALE: gender=male	0.010	0.728^{ns}
LAGE: age in logarithm	-0.036	-1.188^{ns}
Educational level and experience		
EDUC1: inferior or equal to "brevet" diploma	-0.028	-1.213^{ns}
EDUC2: between "brevet" and vocational training certificate	-0.015	-0.7145^{*ns}
EDUC3: equal to A-level	0.013	0.545***
EDUC4: university	ref	
EXP: having a previous professional experience	0.057	2.602***
Job search context		
ALLOC: having received unemployment benefits	-0.019	-1.241^{ns}
DATE1: leaving unemployment in 1995	0.014	0.783^{ns}
DATE2: leaving unemployment in 1996	0.016	0.861^{ns}
DATE3: leaving unemployment in 1997	ref	
Job and firm characteristics		
AIDE: having a granted job	-0.052	-3.087***
CDD: having a non-permanent job	-0.009	-0.516^{ns}
INTERIM: having a temporary job	-0.062	-3.114***
CDI: having a permanent job	ref	
PME: working in a small firm	-0.048	-3.689***
OUVR: being blue-collar	-0.465	-22.279***
OUVRQ: being skilled blue-collar	-0.336	-15.632***
EMPLOY: being employee	-0.411	-22.865***
PRINTER: being executive	ref	
SECTEUR1: working in agricultural sector	ref	
SECTEUR2: working in industrial sector	0.060	1.811*
SECTEUR3: working in service sector	0.014	0.575^{ns}
PNETW: estimated probability of using networks	0.115	1.486^{ns}
$R^2 = 0.23$. Number of observations: 2510		

Data Source: TDE-MLT survey (DARES)

***: significant at 1%. **: significant at 5%. *: significant at 10%.