Transitions and Occupational Changes in a West African Urban Labour Market: The Role of Social Network

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Abstract –

This paper sheds light on the role of social networks in the dynamics of workers in an urban labour market of a West African country. We examine the extent to which one's network is essential in labour market transitions, in particular from unemployment to employment, from wage employment to self-employment, or from self-employment to wage employment. In addition, this paper investigates which dimension of the social network has the main effect on these transitions, by distinguishing quantity and quality of the network. For this purpose, we use a first-hand survey conducted in 2009 in Ouagadougou on a representative sample of 2000 households. This survey provides event history data and very detailed information on social networks. To estimate labour market transitions and job changes, we rely on survival analysis that makes use of proportional hazard models for discrete-time data. We find that social networks have a significant effect on the dynamics of individuals in the labour market and that this effect differs depending on the type of transition considered. In particular, the "quality" of the social network seems to limit transitions from one type of occupation to another, and to encourage workers to evolve within the same type of occupation. By contrast, the size of the social network ("quantity") may promote wider occupational changes, in particular the transition from self-employment to wage employment, which often goes hand in hand with migration to the capital city. These results suggest that the size of the social network conveys information but is not sufficient to improve the occupational status of workers. Considering both quantitative and qualitative dimension of the social network is therefore crucial in assessing the effect of such network on labour market transitions.

JEL-Codes: D13, D61, O12.

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1. Introduction

A significant sociological and economic literature has already emphasized the widespread use of friends, relatives, and other acquaintances to search for jobs, access coveted positions or to help employers locate prospective employees. The seminal work of Granovetter (1973) develops the idea that the labour market outcomes of using social contacts depend on the link between individuals and their contacts, and more precisely on the strength of their tie. Granovetter defines strong ties as links with nearby people – family and friends – that involve repeated and frequent interactions on a number of different levels. More precisely, the strength of a social tie is a *"combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie"* (Granovetter, 1973, p.1361). Links with infrequent interactions or with low intimacy, the weak ties, tend to bridge individuals across social groups of close interpersonal relationships. Granovetter brought out "the strength of weak ties" that means that weak ties are the most informative and thus the most useful for finding a job. While information from strong ties is likely to be very similar to the information one already has, weak ties are more likely to open up information sources that are very different from one's own.

A recent economic literature has also emphasized the role of social networks in labour market outcomes by conveying information about employment, market opportunities or new technology (Durlauf and Fafchamps, 2005; Ioannides and Loury, 2004). This issue is decisive in developing countries where a large part of inefficiency in the labour market may be due to imperfect information. These countries are often characterized by a lack of formal institutions channeling information about jobs. In Ouagadougou (Burkina Faso) for example, 85 percent of unemployed workers are not registered in the public employment office and 45 percent of them declare that this is because they do not know it does exist (DIAL, 2007). In the absence of formal institutions, the role played by interpersonal relationship may then be substantial.

While there are strong evidence on the importance of social networks in labour markets in developing countries, little is known in these countries about the effect of social networks on the dynamics of employment. Besides, researchers remain divided on the features of social networks that have an effect on the labour market in developing countries, and especially on individuals' occupational trajectories, in particular in Africa.

A crucial question tackled in this paper is then to what extent and why different sorts of social networks may lead to different occupational trajectories. This paper aims then at disentangling the determinants of occupational changes by emphasizing the role played by social networks in stabilizing or helping workers enhancing their professional situation.

The objectives of this paper are twofold. First, we analyze the effect of social networks on occupational transitions in Ouagadougou. We seek to answer the following questions. Are social networks one of the resources needed to improve the workers' occupational status? More specifically, to what extent is personal relationship essential in the transition from wage employment to self-employment or from self-employment to wage employment? Do social networks help unemployed individuals access employment?

Second, characterizing the network allows us to better understand the channels of the effect of social networks on professional transitions. For each sort of occupational transitions, we thus examine in a second step the composition of the social networks mobilized.

The paper is organized as follows. Section 2 presents the data we used in this analysis. Section 3 summarizes the estimation strategy. Section 4 analyses the effect of social networks on professional transitions and Section 5 concludes.

2. Data and definitions

Sample definition

For this analysis, we use an original survey conducted in 2009 in Ouagadougou on a representative sample of 2000 households. This survey was conducted by a team of IRD researchers (French Institute of Research for Development) directed by Daniel Delaunay and Florence Boyer (Boyer and Delaunay, 2009) and including the authors of this paper. This survey provides data on socio-demographic characteristics of the households and their members and also on individual events such as work experience and migration history, family trajectories and reproductive histories. In addition, the survey includes very detailed information on social networks that we will describe below. An area sampling methodology guarantees the representativity of the survey. In a first step, we have set the limits of the city. Then, the city was divided into small sub-areas which were randomly sampled. Each of the chosen sub-areas was then fully inspected and enumerated, and one of the households of the sub-area was chosen at random. All the individuals of the household were surveyed. Event history and social network information were collected among half of the individuals aged 18 and over, chosen at random[1]. Thus, we collected work histories of 1762 men and 1050 women totalling 2812 individuals.

Social network characteristics

A social network is a social structure made of nodes (which are generally individuals or organisations) that are tied by one or more specific types of interdependency, such as kinship, friendship, values, beliefs, conflict or trade. In this paper, we restrict the definition of social networks to personal networks. A personal network is a set of human contacts known to an individual, by whom he/she expects to be supported in a given set of activities.

Different dimensions of social networks are considered in this paper. Most of them are measured with a name-generating methodology (McCallister and Fischer, 1978). We asked the respondents to provide a list of names of those who had helped them in various situations: throughout schooling[2], in case of extra expenditures (ceremonies, celebration, health problem of a family member) or in case of difficulties to pay current expenditures in the past 12 months, to access

[1] For more details, see Boyer and Delaunay (2009).

[2] The question was: "Apart from your father and your mother, who helped you during your education, either by funding a portion of the tuition, or by hosting you?".

their last job or to improve their current professional activity[3], and to find housing. In addition, the respondents were asked to cite all their siblings from the same mother and father and all the individuals they had helped during the past 12 months. Further questions about the characteristics of the cited person, as well as relationships between them and between the respondent and each of them, provide information for reconstructing the density of the network, the type of ties, and for knowing the socioeconomic statuses of those cited and thus the social resources they may provide.

However, as is often the case with this type of information, social network characteristics can be thought of being endogenous to labour market choices if one chooses his/her network as a way to get access to certain resources or professional situation. To limit endogeneity and timing problems, in particular the fact that we observe the social network at the time of the survey (or more precisely at the time of the workers' last job change), we essentially rely on information about the siblings, instead of using information concerning the entire social network. Five types of variables are computed in this regard: the total number of declared individuals in the network and the number of siblings that aims at characterizing the network size; the average and maximum years of schooling of the siblings, which is believed to reflect the "quality" of the potential help coming from the siblings; dummies taking value one if a member of the network or of the siblings has a job in the public sector, which is supposed to capture another aspect of the network quality, in particular resources embedded in one's network; the number of siblings living in Ouagadougou or abroad and an index of the geographical scattering of the siblings[4] to measure the fragmentation of the network; and the number of people that were helped by the respondent, which aims at reflecting the strength of ties in its reciprocal aspect.

In addition, we use two variables to measure the intensity of family and kinship networks that are supposed to limit the endogeneity bias: first, a dummy taking value one if the individual had at least one visit to his/her parents (or extended family) over the past week[5]. This variable is believed to capture the intensity of the individuals' relationship with the family but also the reciprocity of the individuals toward their family. Second, we proxy the geographical distance to the worker's locality, village or province of origin. For this variable, instead of relying on a geographical distance *per se* calculated in kilometers (that can be computed from Ouagadougou to the village or commune of origin using geographical maps), we collected directly information from the main bus stations of Ouagadougou about the time and costs necessary to reach the closest main city in the corresponding province of Burkina Faso. This ensures that we are effectively approaching a (time or monetary) cost to keep in touch with the remote family, in a context where roads could be very different shapes.

[3] For the self-employed, the question was: "Who helped you to create or improve your current activity, by helping you to invest?"; and for the wage workers: "Who helped you to find your last job, by advising you, informing you of opportunities, by recommending or hiring you?".
[4] This index takes the value 1 if all the siblings live in Ouagadougou and more than half live in the same sector of the city than the respondent, 2 if the siblings live in Ouagadougou and less than half live in the same sector of the city than the respondent, 3 if all the siblings live in Burkina Faso and more than half in Ouagadougou, 4 if all the siblings live in Burkina Faso and less than half in Ouagadougou, 5 if more than half of the siblings live in Burkina, 6 if less than half of the siblings live in Burkina Faso.
[5] The survey includes an entire module that aims at measuring all the travels of the respondent during a week.

Labour market transitions

Labour market transitions are measured using work histories. In the work histories, individuals have been asked about their spells of activity and inactivity. Events are declared on an annual basis, so that we do not precisely know the months of the event occurrence. Spells are then converted into durations which are computed in years. Each spell of activity was then characterized by the status of activity (employed versus unemployed), the type of employment (self-employment, wage employment, other), the sector of activity and the type of enterprise (public versus private).

Three different labour market transitions are examined in this paper. The first one is the transition from unemployment to employment (1). The two other transitions can be described as occupational changes: wage employment to self-employment (2), and self-employment to wage employment (3).

Let us briefly describe how we defined the different job changes.

For some individuals, there have been some time out of employment or of the labour market. Should this be included or not in the record of job changes? Kambourov and Manovskii (2008) argue that excluding career breaks would underestimate changes. However, the relationship between occupational changes and breaks in employment probably varies by gender, as for women the change of occupation is often a secondary outcome of a different decision, in particular that of child rearing. As a result, some authors exclude women from their sample (Kambourov and Manovskii, 2008). Other authors keep men and women in the sample but compensate by excluding employment interruptions (Parrado, Caner and Wolff, 2007), which may distort their results. In this paper, we made the choice of excluding women from the analysis.[6] The principal reason for this is that the number of women having known a labour market transition is very small in our sample, which would lead us to estimating very small hazard rates for this category of workers (see the distribution of event occurrences for men and women in

Table 1 below). Another reason is that the survey we use is not a labour force survey (LFS), which would allow identifying activity and inactivity spells with accuracy thanks to the use of a series of appropriate filter questions. Hence, distinction between unemployment and inactivity periods, for instance, is particularly prone to be identified with errors for women in our survey since women usually have less labour force attachment than men.

In addition, as in Mc Keever (2006), we ignore non-consecutive job changes, that is to say transitions that were interrupted by a (long) period of unemployment or inactivity. We do this in order to obtain net estimates of the social network determinants of transitions *between* jobs, i.e.

[6] To check for the existence of gender-specific effects in our results, we still ran regressions for men and women separately, in particular concerning the transition from unemployment to employment where the number of failures is sufficiently large for women. For job changes regressions, we preferred to use interaction terms with the sex dummy variable because the occurrence of job changes is very low for women, and so segmenting the global sample by sex would consist of estimating in many cases a very small probability of failure. The results of these exercises are not discussed in this paper for lack of space but are available from the authors upon request.

net from the determinants resulting from transitions between inactivity (or unemployment) to new jobs, the latter transitions having different interpretations in terms of the social network mobilized. In so doing, the drawback is that we may ignore transitions that were preceded by short withdrawals from activity, i.e. those transitions which were unavoidably broken up by frictional unemployment, or by the time to get information about new jobs and to mobilize the social network. In order to keep such transitions in the sample, we still consider as "consecutive" transitions between two jobs that are interrupted by at most two years of unemployment or inactivity. This allows recovering frictional transitions, but still neglects long-term labour market withdrawals (or unemployment of discouraged workers).

Table 1 : Characteristics of Transitions, by Sex

Labour Market Transitions	Number of spells	Number of event occurrences (failures)	Mean length in years if failure
(1) Unemployment to employment			
Overall	715	320	10.3
Men	224	116	6.4
Women	491	204	13.4
(2) Wage employment to self-employment			
Overall	1250	180	10.4
Men	996	167	10.4
Women	254	13	9.0
(3) Self-employment to wage employment			
Overall	1351	130	11.3
Men	915	119	11.4
Women	436	11	10.3

Source: Ouaga2009 survey, authors' calculation.

Finally, we treat each respondent's job spell as a separate case for analysis, meaning that the observation unit is transitions or job changes, not individuals. While this means that men may potentially appear in the sample many times, the majority of men have in fact very few job transitions (see the distribution of these transitions in Table 2 below).

Table 2. Distribution of Men by Number of Transitions

N of transitions in the labour market	Proportion of men (%)	N of occupation-al changes	Proportion of men (%)
0	46.3	0	52.6
1	35.1	1	37.0
2	12.0	2	7.2
3	4.4	3	2.5
4 and more	2.3	4 and more	0.7
Overall	*100*		*100*
N obs	*1762*		*1762*

Source: Ouaga2009 survey, authors' calculation.

Survey limits

Note that we do not measure secondary jobs with our survey. In other words, we count the number of workers in different types of jobs/occupations and not the number of jobs/occupations for the workers. Let us clarify the possible consequence of this. If multi-activity were high among workers and if job changes were higher in secondary jobs, then we would most probably underestimate the extent of job changes in the considered population. Our numbers of labour market transitions should then be considered as lower bounds of the total number of job transitions experienced by workers over their life time. However, from the Phase 1 of the *123 Survey* (Phase 1 is a LFS) in Ouagadougou in 2002, one can show that less than 9 percent of the employed individuals declared a second activity (Bocquier et al., 2010). Then, we believe that this problem is not too severe. Moreover, using the main activity of the worker is easier to understand and, in a comparative perspective, it fits better with the results of previous studies.

Another important drawback of our data is that we have no way to correctly distinguish formal from informal employment, neither at the firm nor at the worker level (see Hussmanns, 2004). This means that we do not differentiate occupations in the formal and informal sectors. However, some recent studies have shown that using the divide of self-employment, wage-employment and contributing family helpers at the worker level in urban West Africa is still a meaningful way of characterizing the quality and vulnerability of jobs in these cities (see Bocquier et al., 2010).

An often mentioned potential issue with survival analysis is the memory problem of the respondents. It relates to whether memory and recall bias on labour market history could affect the results. If recall problems are worse for certain types of workers (unskilled versus skilled, due to longer spells of work of the former; women versus men because women may have more events to recall than men due to their less continuous labour market participation), recall bias may lead the workers to underestimate or overestimate their actual labour market experience. In this paper, we use a potential experience variable as a regressor to mitigate this problem. This potential experience variable is not computed from the respondents' age, years of schooling, and age at school entry (as it is usually the case with LFS), but makes use of the property of the event history data: we do observe the actual age at the labour market entry and so can just deduct it from the age at the date of the survey. This provides us with a "quasi-potential" experience variable. This variable is one of the time-varying covariates in the hazard models presented in the next section.

In addition, note that the method used to obtain the data should result in minimal recall bias since, rather than asking respondents what they did in any given year, the interviewers asked them to think sequentially through their personal histories. While this technique cannot eliminate all potential problems, overall these should be minimized due to the fact that job changes are rare and major events in a person's life and, as such, respondents are likely to recall them with some accuracy. The memory problem in event history surveys should not be overstated as shown by Poulain et al. (1992) in their paper matching biographical survey data and administrative registers at the individual level in Belgium.

3. Estimation strategy

The hazard models

To estimate labour market transitions and job changes, we rely on a survival analysis that makes use of proportional hazards models for discrete-time data. The hazard rate characterizes individuals' propensity to leave a state after a certain spell duration *t*, given that an escape from this state did not occur prior to *t*. Since our event history dataset records year events for each individual since birth, we do not know the exact time of failure in months, but just a year interval in which the failure occurred. Hence, our survival times are interval censored rather than intrinsically discrete. For this reason, we prefer the complementary log-log model, also called the *cloglog* (see Jenkins, 2005 for further details).

Let us define a general case of hazard rate θ (t, X_t), i.e. the hazard rate at survival time t for a person with time-varying covariates summarised by a vector X_t. We can derive an estimate of parameters describing a continuous time hazard, but taking into account the nature of the banded survival time data that is available to us.

The survivor function at time *t* is given by:

$$S(t, X_t) = \exp\left[-\int_0^t \theta(u) du\right] \quad (1)$$

$$= \exp\left[-\int_0^t \theta_0(u) \exp(\beta' X_u) du\right] \quad (2)$$

with $\theta_0(t)$ the baseline hazard function which depends on *t*.

Let us define $\lambda = \exp(\beta' X_t)$ a person specific non-negative function of time-varying covariates *X*, which scales the baseline hazard function common to all persons. The discrete-time hazard function for interval $(a_{j-1}, a_j]$, $h(a_j, X_j) = h_j(X_j)$, is defined by

$$h_j(X_j) = \frac{S(a_{j-1}, X_{j-1}) - S(a_j, X_j)}{S(a_{j-1}, X_{j-1})}$$

$$= 1 - \frac{S(a_j, X_j)}{S(a_{j-1}, X_{j-1})}$$

$$= 1 - \exp[\lambda(H_{j-1} - H_j)] \qquad (3)$$

where $H_j = H(a_j) = \int_0^{a_j} \theta_0 (u, X) du$ is the integrated baseline hazard evaluated at the end of the interval.

Rewriting expression (3) in log gives $\log(1 - h_j(X_j)) = \lambda(H_{j-1} - H_j)$ which can be further expressed as

$$\log(-\log[1 - h_j(X_j)]) = \beta' X_j + \log(H_j - H_{j-1}) = \beta' X_j + \gamma_j \qquad (4)$$

where γ_j is the log of the difference between the integrated baseline hazard $\theta_0(t)$ evaluated at the end of the interval $(a_{j-1}, a_j]$ and the beginning of the interval.

The log(-log(.)) transformation (4) is known as the complementary log-log (*cloglog*) and gives

$$h(a_j, X_j) = 1 - \exp[-\exp(\beta' X_j + \gamma_j)]. \qquad (5)$$

If each interval is of unit length, which is the case in our event history data, then time intervals become interval numbers rather than dates marking the end of each interval. Expression (4) can then be rewritten as

$$h(j, X_j) = 1 - \exp[-\exp(\beta' X_j + \gamma_j)]. \qquad (6)$$

This *cloglog* model is a form of generalized linear model and is appropriate for interval-censored survival data. Complementary log-log models are also frequently used when the probability of an event is very small or very large.

One alternative of *cloglog* models could be the logistic model. The advantage of *cloglog* model is that it is a discrete-time equivalent of the widely used Cox proportional hazard model. In practice, *cloglog* and logistic hazard models that share the same duration dependence specification and the same X yield similar estimates as long as the hazard rate is relatively "small" (Jenkins, 2005).[7] We tested whether it was indeed the case with our data and found evidence that our results were qualitatively unchanged with logistic regressions.

Let us now detail the regressors introduced in the hazard regressions. Three vectors of explanatory variables are considered. The first one corresponds to individuals' socio-demographic characteristics that are assumed to be fixed over the survival time considered (called X_1). It then reveals the individuals' situation at the date of the survey. X_1 includes a dummy for sex, a dummy

[7] Indeed, one can show that with a sufficiently small hazard rate, the proportional odds model (a linear function of duration dependence and characteristics) is a close approximation to a model with the log of the hazard rate as dependent variable.

for being Muslim, another for belonging to the majority ethnic group (Moore), and the level of schooling. An additional controls is introduced for the occupational transitions: a dummy indicating whether the worker was employed in the agricultural sector. We also use time-varying covariates (X_{2j}) which comprise the individuals' potential experience in the labour market, the time elapsed since the individual arrived in Ouagadougou (which is equal to the survival age for non-migrants), the time elapsed since first marriage (equal to zero for non-married individuals), and the time elapsed since first child birth (equal to zero for individuals with no children).

Finally, we introduce the vector of variables characterising the individuals' social network at the time of the survey (*SN*). These variables are described in the data section. We realize that trying to explain past events by current state variables might be problematic. The problem is that we cannot observe the individuals' social network at each survival period and so we have to assume that the social network's characteristics did not vary too much over time. As it might still be a strong hypothesis, we decide to rely essentially on variables describing the characteristics of the sibling, which is less subject to changes over the individuals' professional career. Another advantage of focusing on the siblings is that it is a more exogenous component of the individuals' social network.

The *cloglog* function that we estimate can now be written as

$$h(j, X_j) = 1 - \exp\left[-\exp(\beta_1' X_1 + \beta_2' X_{2j+} \delta' SN + \gamma_j)\right] \quad (7)$$

In the models considered so far, all differences between individuals were assumed to be captured using observed explanatory variables. We then allow for unobserved individual effects in the models. In the bio-medical sciences which model survival times, they are usually referred to as 'frailty', which corresponds to an unobserved propensity to experience an adverse health event. In the case of labour market transitions and job changes, ignoring unobserved heterogeneity may result in different biases (Jenkins, 2005): first, non-frailty model may over-estimate the degree of negative duration dependence in the true baseline hazard, and under-estimate the degree of positive duration dependence. In other words, other things being equal, a selection effect may induce individuals with high values of unobserved heterogeneity (or more capable workers) to fail faster (i.e. to exit from unemployment or to obtain better jobs faster). In such case, the survivors at any given survival time are increasingly composed of observations with relatively low values of unobserved heterogeneity (discouraged or unmotivated workers) and then lower hazard rates. Second, the proportionate effect of a given regressor on the hazard rate (β) is no longer constant and independent of survival time. Third, the presence of unobserved heterogeneity may yield an underestimation of any positive β derived from an uncorrected model, and reciprocally an overestimation of any negative effect (Lancaster, 1990).

With u denoting a random variable with a mean of zero and finite variance, the model specification for a frailty hazard rate may simply be written as

$$h(j, X_j) = 1 - \exp\left[-\exp(\beta_1' X_1 + \beta_2' X_{2j+} \delta' SN + \gamma_j + u)\right] \quad (8)$$

The random variable u may be interpreted in several ways. The most common interpretation is that it summarises the impact of omitted variables on the hazard rate. Alternative readings are usually measurement errors in the recorded regressors or recorded survival times. To estimate this model, we require expressions for density and survival functions that do not condition on the unobserved effects. This is generally called 'integrating out' the unobserved effect. For the discrete-time proportional hazard model (*cloglog*), the Gamma distribution has been one of the most popular distributions. This is the approach we follow by using a maximum likelihood estimation of the proportional hazard models incorporating a Gamma mixture distribution to summarize unobserved individual heterogeneity (see Jenkins, 2005).

Analysis of social networks using a principal component analysis

We use a principal component analysis (PCA) to summarize the observed information about the men' social network. In principal component analysis[8], a set of variables is transformed into orthogonal components, which are linear combinations of the variables and have maximum variance subject to being uncorrelated with one another. Typically, the first few components account for a large proportion of the total variance of the original variables, and hence can be used to summarize the original data. The computed factors were rotated using an oblique rotation to ease their interpretation. There are two possible uses of factor analysis in this context. First, we use the PCA results as a guide to identify the most influential and/or meaningful social network variables in our data. These resulting variables (*SN*) are then directly introduced as explanatory variables in the labour market transition regressions. Second, following Dickerson and Green (2004), Jellal et al. (2008) or Fernandez and Nordman (2009) in other contexts, we make use of the generated PCA axes as substitutes for social network variables in the labour market changes regressions. By construction, these axes have indeed the advantage of being orthogonal to each other, therefore circumventing potential multicollinearity issues which might be important in the case of social network characteristics. More importantly, if one can provide a qualitative interpretation of each of the PCA axes, thereby reflecting the different dimensions of the individuals' social network, then one might be able to make sense of their potential effects in a multivariate analysis where they are used as explanatory variables.

Table 4 in Appendix reports the main diagnostics of this PCA. Further details on this PCA can be obtained from the authors upon request. The eigenvalues corresponding to the first six factors are larger than one, and altogether the ten factors account for 96 percent of initial total variance. Factor loadings were rotated using an oblique rotation since it is clear that the factors may be correlated. For our purpose, the first six inertia axes - the estimated factors which are linear components of all the social network' characteristics described in the data section - concentrate a large proportion of the total variance of the original variables (78 percent) and reflect, therefore, a fair amount of the relevant information about the individuals' social network characteristics. The other factors represent a negligible amount of the statistical information and are dropped from the analysis.

[8] We have tried other techniques of factor analysis, such as the principal factor method, which leads to similar results.

The pairwise correlation coefficients of the social network's and individual's main characteristics and with the first six factors are then used for the interpretation of the computed factors (

Table 5 in Appendix). The six factors are closely associated with the following characteristics: Factor 1 corresponds to the distance to the region or village of origin, which is highly correlated to two variables describing the costs (in CFA francs) and time (in hours) necessary to travel to the individual's locality of origin. Factor 2 reflects the network size, i.e. the total number of declared individuals in the network and the number of siblings. Factor 3 emphasizes the educational level of the network, in particular the average years of schooling and the maximum years of the siblings. The activity portfolio of the network is strongly represented by Factor 4, in particular whether its members have a job in the public sector. Factor 5 is highly correlated to information summarizing the fragmentation of the network, especially whether siblings live in Ouagadougou and abroad, and the share of the siblings living in the neighbourhood. Finally, Factor 6 reflects aid reciprocity and intensity of the relationship as it is highly correlated to the number of visits to the kin and friends the past year, and also to the number of people that were helped by the individual.

These six factors therefore reflect a wide range of social network characteristics. Moreover, we find that the factors have all a rather clear interpretation.[9] These network characteristics can mainly be described by the network's size, education, geographical remoteness, professional activity of its members, fragmentation and reciprocity.

4. Results

Table 6 in Appendix presents the estimation results for the three transitions. For each transition, Models 1 and 2 estimate hazard rates without controlling for the time-invariant unobserved heterogeneity of individuals (non-frailty models). In addition, Models 3 and 4 report the frailty estimates. Social networks are approximated by the most influential social network variables in Models 1 and 3, and by the computed Factors resulting from the PCA in Models 2 and 4 (see previous section).

Transition from unemployment to employment

Only one dimension of the network has a significant effect on the propensity to find a job when individuals are unemployed: the distance to the area of origin (Model 1, Table 6). Its effect is significant and positive. This effect does also hold if we regress the model by taking into account the time-invariant unobserved heterogeneity of individuals (Model 3 in Table 6). However, Factor 1, reflecting the distance to the region or village of origin, has only a weak effect in Models 2 and 4, which might be attributed to the specificity of this type of regressions where social network characteristics are summarized and therefore diluted in only a few estimated regressors.

This may suggest that a longer distance between the unemployed and his/her kin in the village of origin leads to higher motivation to find a job. This may happen because the longer the distance, the higher the costs for the kin to observe the occupational earnings of the worker. Demands

[9] Naturally, as it is always the case in factor analysis, these interpretations are somewhat subjective. The reader may substitute her own if wished.

from the village or more generally from the kin in the area of origin seems to have a disincentive effect on the job search and this effect get diluted with geographical distance.

Thus, we find that social networks do not help unemployed to find a job in the context of Ouagadougou. On the contrary, it may exert a redistributive pressure that leads unemployed to limit their effort to find a job.

This result is very different from what is generally observed in developed countries (Bentolila et al. 2010). This may be due to different meanings of being unemployed in the African context, where underemployment more accurately summarizes the different forms of distortion on the labour market and where there is no unemployment insurance.

One the contrary, this result is very close to that of Grimm et al. (2010) concerning the resource allocation and value added of informal entrepreneurs in seven West-African capitals, including Ouagadougou. The authors find robust negative effects associated with social ties in the village of origin and observe that these effects decrease with geographical distance.

Transition from wage employment to self-employment

As shown in Table 6, social network has no effect on the propensity to experience a transition from wage employment to self-employment, when non-frailty models are considered (Models 1 and 2). But this result does not hold anymore if we control for unobserved individual effects in the models. As frailty models mitigate time-invariant unobserved heterogeneity bias, we limit the interpretation to these models. The activity portfolio of the network has a negative and significant effect and this whatever its specification (either Factor 4 or dummy taking value one if a sibling has a job in the public sector): for wage employed, having a member of the network in the public sector decreases the propensity to become self-employed. In addition, Factor 5, reflecting the fragmentation of the siblings, has a negative and significant effect on the propensity to experience such a transition.

Taken together, these results suggest that having a "high quality" network, in particular strength ties in the public sector, concentrated in Ouagadougou, makes the choice to evolve inside wage employment more advantageous than the one to move to the more hazardous status of self-employed. In other words, the resources embedded in a network linked to public sector may be more profitable inside wage employment than in self-employment occupations.

The hazardous aspect of self-employment is confirmed by the negative and significant effect of having children on the transition to self-employment.

Transition from self-employment to wage employment

We denote large effects of social networks on the propensity to experience a transition from self-employment to wage employment (Table 6): the size of the network has a positive and significant effect, whether it is measured by the siblings size or by Factor 2; the fragmentation of the siblings has a positive effect as well; on the contrary, quality of the network, captured by its average education level, has a negative and significant effect on this propensity.

Moreover, it appears that recent migrants, in particular those who were farmer previously, are more concerned with this transition, since being self-employed in the agricultural sector and the time elapsed since the individual arrived in Ouagadougou have both a significant effect, positive in the first case, negative in the second.

Thus, a larger network seems to allow self-employed to get a better access to information on wage employment opportunities or to be recommended. The more fragmented the network, the wider the information received.

If geographical distance to the kin could be considered as one dimension of the strength of tie, these evidences suggest that the "strength of the weak ties" matters to find a wage employment. By contrast, having a good quality network may encourage workers to evolve as self-employed. Indeed, in some cities and activities of West Africa, it is not uncommon to see unregistered self-employed workers, therefore belonging to the informal sector, following some of the management rules of modern enterprises. A few authors have thus identified an "upper segment" of the informal sector, which would be less vulnerable in terms of earnings than the bulk of wage-employment situations (see Fields, 2004; Bocquier et al., 2010).

Table 3. Synthesis of hazard models estimations

Transitions	Unemployment to Employment		Wage Employment to Self-employment		Self-employment to Wage Employment	
Type of model	Non-frailty model	Frailty model	Non-frailty model	Frailty model	Non-frailty model	Frailty model
Siblings'average years of schooling	0	0	0	0	-	-
Siblings size	0	0	0	0	+	+
Siblings in public sector	0	0	0	-	0	0
Distance to birthplace (hours)	+	+	0	0	0	0
Siblings'geo. scattering	0	0	0	0	0	0
Visit to parents	0	0	0	0	0	0
Factor 1 (distance to the birth place)	0	0	0	0	0	Do not converge
Factor 2 (network size)	0	0	0	0	+	
Factor 3 (network education)	0	0	0	0	-	
Factor 4 (network activity)	0	0	0	-	0	
Factor 5 (fragmentation)	0	0	0	-	+	
Factor 6 (reciprocity)	0	0	0	0	0	

Source: Ouaga2009 survey, authors' calculation.

5. Conclusion

The aim of this paper is to shed light on the role of social networks in the dynamics of the urban labour market, in the context of a West African country. The crucial issue tackled in this paper is the extent to which one's network is essential in labour market transitions, in particular from unemployment to employment, from wage employment to self-employment, or from self-employment to wage employment. In addition, this paper investigates which dimension of the social network has the main effect on these transitions, by distinguishing quantity and quality of the network.

For this purpose, we use an original survey conducted in 2009 in Ouagadougou on a representative sample of 2000 households. This survey provides event history data and very detailed information on social networks. To estimate labour market transitions and job changes, we rely on survival analysis that makes use of proportional hazard models for discrete-time data.

We find that social networks have a significant effect on the dynamics of individuals in the labour market. However, this effect is very different depending on the type of transition considered. In the cases of transition from unemployment to employment or from wage employment to self-employment, social networks have a negative effect on the propensity to experience such transitions.

Social networks do not help unemployed workers find a job in the context of Ouagadougou. It may exert a redistributive pressure that leads the unemployed to limit their effort to find a job, but this effect weakens with geographical distance. The complete contrast to what is generally observed in developed countries may be due to a large share of underemployment.

As far as transitions from wage employment to self-employment are concerned, having a "high quality" network, in particular strong ties to the public sector, reduces the propensity to transit. On the contrary, the social network has a positive effect on the transition from self-employment to wage employment, when its quantitative dimension is considered. A larger network increases the propensity to find a wage job for self-employed workers while having a good quality network has the opposite effect.

The quality of the social network therefore seems to limit transitions from one type of occupation to another, and to encourage workers to evolve within a type of occupation. Further research is needed to test whether good quality social networks really does help workers climb the professional ladder within the aggregate occupation types considered in this paper. By contrast, the size of the social network may promote wider occupational changes, in particular the transition from self-employment to wage employment, which often goes hand in hand with migration to the capital city. These results suggest that the size of the social network conveys information but is not sufficient to improve the occupational status of workers. It should be recalled that these results hold when very aggregate occupation types are considered and thus when occupational changes are substantial. Considering both quantitative and qualitative dimension of the social network is therefore crucial in assessing the effect of such network on labour market transitions.

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Appendix

Table 4. Principal component analysis (PCA) of social network characteristics

Factors	Eigenvalues	Difference	Proportion	Cumulative
Factor1	3.38178	0.79699	0.2416	0.2416
Factor2	2.58478	0.86930	0.1846	0.4262
Factor3	1.71548	0.52974	0.1225	0.5487
Factor4	1.18574	0.07183	0.0847	0.6334
Factor5	1.11391	0.10969	0.0796	0.7130
Factor6	1.00422	0.10377	0.0717	0.7847
Factor7	0.90045	0.11197	0.0643	0.8490
Factor8	0.78848	0.28552	0.0563	0.9053
Factor9	0.50296	0.20158	0.0359	0.9413
Factor10	0.30138	0.06986	0.0215	0.9628
Factor11	0.23152	0.06044	0.0165	0.9793
Factor12	0.17109	0.08867	0.0122	0.9916
Factor13	0.08241	0.04664	0.0059	0.9974
Factor14	0.03578	.	0.0026	1.0000

Source: Ouaga2009 survey, authors' calculation.

Table 5. Pairwise correlation coefficients between PCA factors, social network and individual characteristics

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
	Distance to the origin locality	**Size of the network**	**Education of the network**	**Activity portfolio of the network**	**Fragmen-tation of the siblings**	**Reciprocity**
Social network characteristics						
Visit to parents	0.1717*	0.0762*	-0.1850*	0.2630*	-0.1480*	**0.6815***
Visit to friends	-0.0449	0.0832*	0.2677*	-0.0997*	0.1213*	**0.6738***
Network size	0.1922*	**0.8656***	0.0417	0.2133*	0.0702*	0.2760*
Number of people helped by Ego	0.2835*	0.3542*	-0.2989*	0.3226*	-0.1773*	**0.5139***
Siblings size	0.0390	**0.8979***	0.2709*	0.1199*	0.1000*	0.0065
Number of siblings in Ouaga	-0.2828*	0.5880*	0.3412*	0.0074	-0.5939*	-0.0668*
Number of siblings abroad	0.3475*	0.2619*	0.1682*	-0.0603	**0.7570***	0.0125
Siblings'geo. scattering	0.3506*	0.0614	-0.0949*	0.1011*	**0.8796***	0.0425
Distance to birthplace (hours)	**0.9583***	0.0503	0.0774*	0.1606*	0.3831*	0.0919*
Distance to birthplace (CFA)	**0.9551***	0.0805*	0.1226*	0.1557*	0.3607*	0.0978*
Siblings'average years of schooling	0.1499*	0.1770*	**0.8591***	0.3516*	-0.0544	0.0502
Siblings'max years of schooling	0.1685*	0.3327*	**0.8485***	0.3795*	-0.0210	0.0712*
Siblings in public sector	0.1177*	0.2089*	0.3954*	**0.8383***	0.0130	-0.0039
Network members in public sector	0.1740*	0.1558*	0.2559*	**0.8903***	0.0082	0.1263*
Individual characteristics						
Aged 26-35	0.0084	0.1241*	0.1193*	-0.0103	0.0047	0.0045
Aged 45 and over	0.0173	-0.2583*	-0.2324*	0.0402	0.0185	-0.0032
Islam religion	0.0333	-0.0551	-0.1608*	-0.1583*	-0.0006	-0.0423
Moore ethnie	-0.3615*	-0.0397	-0.1545*	-0.1814*	-0.2033*	-0.0912*
Born in Ouaga	**-0.5558***	0.0887*	0.2421*	-0.1097*	-0.3679*	-0.0458
Primary school	-0.0571	0.0496	0.0301	-0.0725*	-0.1161*	0.0220
Lower secondary school	-0.0029	0.0233	0.1899*	0.0324	-0.0267	0.0014
Higher secondary school and above	0.2302*	0.1680*	**0.3806***	**0.3308***	0.0974*	0.1126*

Source: Ouaga2009 survey, authors' calculation. *Note*: * means significant at the 1% level.

Table 6. Hazard regressions results

	Unemployment to Employment				Wage Employment to Self-Employment				Self-Employment to Wage Employment		
VARIABLES	(1) Non-frailty model	(2) Non-frailty model	(3) Frailty model	(4) Frailty model	(1) Non-frailty model	(2) Non-frailty model	(3) Frailty model	(4) Frailty model	(1) Non-frailty model	(2) Non-frailty model	(3) Frailty model
Individual characteristics											
Muslim	0.280	0.293	0.395*	0.426*	0.134	0.108	0.101	0.0623	-0.301	-0.269	-0.504**
	(0.219)	(0.217)	(0.228)	(0.233)	(0.178)	(0.178)	(0.204)	(0.194)	(0.209)	(0.208)	(0.235)
Moore	0.00321	-0.0334	0.00188	-0.0568	0.0519	0.0563	0.0693	0.0570	0.167	0.165	0.237
	(0.251)	(0.251)	(0.244)	(0.261)	(0.270)	(0.273)	(0.458)	(0.243)	(0.331)	(0.338)	(0.370)
Primary school	0.716**	0.658**	0.523	0.486	0.0691	0.0565	0.115	0.103	0.491*	0.524**	0.502*
	(0.310)	(0.301)	(0.318)	(0.336)	(0.221)	(0.224)	(0.254)	(0.240)	(0.262)	(0.264)	(0.302)
Lower secondary school	0.299	0.206	0.226	0.183	-0.492	-0.488	-0.262	-0.257	0.954**	0.975**	1.452***
	(0.366)	(0.359)	(0.372)	(0.381)	(0.352)	(0.353)	(0.379)	(0.355)	(0.420)	(0.422)	(0.442)
Higher secondary school & above	1.098***	1.048***	0.939**	0.976**	-0.825**	-0.826**	-0.676*	-0.644*	0.883	0.898	1.341**
	(0.362)	(0.371)	(0.369)	(0.407)	(0.348)	(0.348)	(0.384)	(0.359)	(0.578)	(0.577)	(0.598)
Potential experience (years)	0.0490	0.0456	0.0309	0.0286	0.0616**	0.0611**	0.0645*	0.0649***	0.0545*	0.0542*	0.0689***
	(0.0303)	(0.0299)	(0.0265)	(0.0298)	(0.0254)	(0.0254)	(0.0344)	(0.0170)	(0.0297)	(0.0296)	(0.0231)
Potential experience squared	-0.00288***	-0.00274***	-0.00224**	-0.00210**	-0.00139**	-0.00137**	-0.00137	-0.00136***	-0.000827	-0.000779	-0.000879
	(0.00107)	(0.00104)	(0.000917)	(0.00101)	(0.000658)	(0.000654)	(0.000851)	(0.000473)	(0.000682)	(0.000683)	(0.000537)
Time since arrival in Ouaga	0.0162	0.0176	0.0188*	0.0196	0.00583	0.00603	0.0110	0.0101	-0.0186**	-0.0180**	-0.0141
	(0.0126)	(0.0124)	(0.0112)	(0.0133)	(0.00839)	(0.00838)	(0.0115)	(0.00805)	(0.00899)	(0.00890)	(0.00953)
Time since first child birth	-0.0205	-0.0175	-0.0226	-0.0209	-0.0690***	-0.0668***	-0.0664***	-0.0648***	-0.0127	-0.0133	-0.0109
	(0.0244)	(0.0249)	(0.0256)	(0.0270)	(0.0212)	(0.0212)	(0.0218)	(0.0198)	(0.0239)	(0.0238)	(0.0250)
Time since first child marriage	-0.0116	-0.0158	-0.0196	-0.0239	0.0138	0.0117	0.0162	0.0148	-0.0104	-0.0100	-0.00834
	(0.0214)	(0.0215)	(0.0223)	(0.0228)	(0.0206)	(0.0204)	(0.0221)	(0.0199)	(0.0211)	(0.0209)	(0.0217)
Agricultural sector					1.540***	1.534***	1.468***	1.461***	1.289***	1.333***	1.337***
Social network characteristics					(0.198)	(0.198)	(0.230)	(0.220)	(0.229)	(0.229)	(0.257)

Siblings'average years of schooling	-0.0388		-0.0344		-0.00769		0.000991		-0.0719*		-0.108**
	(0.0292)		(0.0311)		(0.0270)		(0.0277)		(0.0398)		(0.0470)
Siblings size	-0.0356		-0.00916		0.0455		0.0364		0.108**		0.140**
	(0.0536)		(0.0521)		(0.0475)		(0.0585)		(0.0546)		(0.0584)
Siblings in public sector	0.175		0.280		-0.475		-0.767**		0.364		0.552
	(0.302)		(0.309)		(0.314)		(0.356)		(0.406)		(0.444)
Distance to birthplace (hours)	0.100*		0.0998**		-0.0249		-0.000379		0.0344		0.0388
	(0.0525)		(0.0486)		(0.0500)		(0.0745)		(0.0554)		(0.0621)
Siblings'geo. scattering	0.0445		0.0245		-0.0716		-0.0900		0.0885		0.102
	(0.0758)		(0.0646)		(0.0723)		(0.0895)		(0.0779)		(0.0835)
Visit to parents	-0.254		-0.227		0.106		0.201		-0.00869		-0.213
	(0.223)		(0.229)		(0.175)		(0.197)		(0.217)		(0.258)
Factor 1		0.181		0.182		0.0148		0.102		0.0760	
		(0.118)		(0.123)		(0.125)		(0.132)		(0.134)	
Factor 2		-0.0551		0.0119		0.0613		0.0122		0.384***	
		(0.0987)		(0.101)		(0.0885)		(0.0937)		(0.105)	
Factor 3		-0.170		-0.174		-0.0840		-0.0743		-0.369**	
		(0.138)		(0.149)		(0.114)		(0.119)		(0.153)	
Factor 4		0.0240		0.0626		-0.157		-0.239**		0.00762	
		(0.0980)		(0.104)		(0.109)		(0.118)		(0.144)	
Factor 5		0.110		0.0677		-0.168		-0.274**		0.165	
		(0.103)		(0.107)		(0.113)		(0.122)		(0.114)	
Factor 6		-0.0107		-0.0534		0.000132		0.0366		-0.179	
		(0.109)		(0.117)		(0.0904)		(0.0964)		(0.127)	
Constant	-2.984***	-2.800***	-3.060***	-2.824***	-4.499***	-4.732***	-4.878***	-5.089***	-6.275***	-5.817***	-6.982***
	(0.562)	(0.379)	(0.399)	(0.394)	(0.508)	(0.384)	(0.971)	(0.279)	(0.645)	(0.502)	(0.591)
ln_varg			-15.75	-15.47			-14.07	-14.13			-12.95
			(567.3)	(564.1)			(563.6)	(518.1)			(397.3)
Observations	1191	1191	1191	1191	11414	11414	11414	11414	11781	11781	11781

Source: Ouaga2009 survey, authors' calculation. *Note*: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.