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TRANSITIONS IN A WEST AFRICAN LABOUR MARKET: THE ROLE OF SOCIAL NETWORKS

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Abstract

This paper sheds light on the role of social networks in the dynamics of a West African labour market, i.e. in the transitions from unemployment to employment, from wage employment to self-employment, and from self-employment to wage employment. It investigates the effects of three dimensions of the social network on these transitions: its structure, the strength of ties and the resources embedded in the network. For this purpose, we use a first-hand survey conducted in Ouagadougou on a representative sample of 2000 households. Using event history data and very detailed information on social networks, we estimate proportional hazard models for discrete-time data. We find that social networks have a significant effect on the dynamics of workers in the labour market and that this effect differs depending on the type of transition and the considered dimension of the social network. The network size appears to not matter much in the labour market dynamics. Strong ties however play a stabilizing role by limiting large transitions. Their negative effect on transitions is reinforced when they are combined with high level of resources embedded in the network.

Key words: Social Network; Kinship; Labour Market Dynamics; Event History Data; Survival Analysis; Burkina Faso.

Résumé

Dans cet article, nous analysons le rôle des réseaux sociaux dans la dynamique d'un marché du travail en Afrique de l'Ouest, en nous intéressant aux transitions du chômage vers l'emploi, de l'emploi salarié vers l'emploi indépendant et enfin de l'emploi indépendant vers l'emploi salarié. Les données d'une enquête originale que nous utilisons permettent d'appréhender les réseaux sociaux dans trois de leurs dimensions, à savoir sa structure, la force des liens et des ressources intégrées dans le réseau, et d'analyser les effets différenciés de chacune de ces dimensions sur ces transitions. Ces données, collectées à Ouagadougou en 2009, rassemblent les biographies professionnelles de 2000 ménages et sont représentatives à l'échelle de la ville. En nous appuyant sur des modèles de risques proportionnels, nous constatons que les réseaux sociaux ont un effet significatif sur la dynamique des travailleurs et que cet effet diffère selon le type de transition et la dimension considérée du réseau social. La taille du réseau semble joué un rôle mineur au regard des deux autres dimensions. Des liens forts jouent un rôle stabilisateur en limitant les grandes transitions. Leur effet négatif sur les transitions est renforcé quand ces liens forts sont combinés à un niveau élevé de ressources du réseau.

Mots Clés : Réseaux sociaux, parentèle, dynamique du marché du travail, enquête biographique, modèle de durée, Burkina Faso.

JEL Code : D13, J24, L14.

1. Introduction

A recent economic literature emphasizes 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). From a theoretical perspective, social networks are known to be crucial to understand the dynamics of labour market, in particular duration dependence and persistence in unemployment (Calvó-Armengol and Jackson 2004, 2007; Bramoullé and Saint-Paul 2010). From an empirical perspective, evidence shows that there is a widespread use of friends, relatives, and other acquaintances to search for jobs and to access coveted positions. For entrepreneurs, social networks may be used to reduce the uncertainties they face regarding market opportunities, reliance of partners, or productivity of their prospective employees, and also to enhance risk-sharing and informal credit arrangements (Hoang and Antoncic 2003).

These issues are 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 or market opportunities. 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 relationships may then be substantial in employment trajectories.

While there is strong evidence on the importance of social networks in labour markets in developing countries, little is known in these countries about the specific effect of different dimensions of social networks. Indeed, most of the studies in developing countries, particularly in Sub-Saharan Africa, focus on the size of social networks, approximated by the number of contacts that an agent maintains with other categories of agents. However, since the seminal sociological work of Granovetter (1973), it is widely acknowledged that the intensity of ties is an essential dimension of social networks. Granovetter brought out 'the strength of weak ties' argument highlighting that links with infrequent interactions or with low intimacy, the weak ties, tend to bridge individuals across social groups of close interpersonal relationships, and are consequently the most informative and the most useful in the labour market. Lin (1990)'s theory of social resources also emphasizes a dimension of social networks that has to be addressed: the resources available in a network, defined by the socio-economic characteristics of the individuals connected through the network.

Some studies have attempted to fill this knowledge gap but they remain divided on the effect of social networks resources and ties content on the labour market. Besides, to the best of our knowledge, they all focus on enterprises outcomes and they do not address the issue of dynamics of employment. With data on Ghanaian enterprises, Barr (2002) supports the proposition that networks affect enterprise performance in different ways depending on the network features. Entrepreneurs with larger enterprises tend to maintain innovation networks that are large, diverse, less cohesive and best suited to providing access to information about technology and markets. In contrast, entrepreneurs with smaller enterprises tend to maintain solidarity networks that are small, homogeneous, cohesive and best suited to reducing information asymmetries and thus supporting informal credit and risk-sharing arrangements.

On the contrary, using an original dataset collected in the informal economy of Bobo-Dioulasso (Burkina Faso), Berrou and Combarnous (2012) find that small informal enterprises are not systematically characterized by small and homogenous networks, and that informal entrepreneurs have to combine strong and wide ongoing social support ties with weaker business ties to be successful.

Other studies conducted mostly by sociologists and anthropologists emphasize the reverse side of strong ties. In her research on informal manufacturers in Nigeria, Meagher (2006) identifies disinclination among entrepreneurs to trade with people from their home communities because they exercise moral pressure to get credit and then expect the trader to understand their problems when the time comes for repayment. In the same way, Whitehouse (2011) find that in the capital of the Republic of Congo, it is especially difficult for entrepreneurs to do business in their home communities, where they face a constant barrage of requests by their kin, both close and distant, for goods on credit, for discounts, for employment, and for short-term loans or grants outright.

The lack of consensus between these studies may be explained by the low representativity level of their observations or data, but also because they failed overcoming the simultaneity issue between network constitution and entrepreneurial success.

In an African context, this paper aims then at disentangling the determinants of changes in the workers' employment status and transitions from unemployment to employment by emphasizing the role played by social networks in stabilizing or helping workers enhancing their professional situation. A crucial question tackled is to what extent and why different sorts of social networks may lead to different employment trajectories. We analyze the effect of social networks on specific employment transitions in Ouagadougou by answering the following questions. Do social networks help unemployed individuals access employment? Are social networks one of the resources needed to improve the workers' employment status? More specifically, to what extent is personal social network essential in the transition from wage employment to self-employment or from self-employment to wage employment? Indeed, using the divide of self- and wage-employment in urban West Africa has been shown to be a meaningful way of characterizing the quality and vulnerability of jobs (Bocquier, Nordman and Vescovo 2010).

We attempt to overcome the limitations of the previous studies on social networks and labour markets outcomes in Sub-Saharan Africa in different ways. First, we avail ourselves of a representative sample of households in the capital of Burkina Faso which combines workers' socio-demographic and very detailed social network information together with event history data, in particular the individuals' employment records.[1] Second, we characterize the personal networks in their various dimensions. Lastly, we take into account the issue of simultaneity bias that may affect the measure of the effect of social networks on labour market outcomes using a survival analysis that makes use of proportional hazard models for discrete-time data.

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

2. Surveys, data and definitions

The surveys

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[2] researchers, including the authors of this paper, under the supervision of Daniel Delaunay and Florence Boyer (Boyer and Delaunay 2009). 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

[1] See Nordman and Roubaud (2009) for an example of labor market analysis using event history data.
[2] French Institute of Research for Development.

individuals aged 18 and over, chosen at random.[3] Thus, we collected work histories of 1762 men and 1050 women totaling 2812 individuals.[4]

In addition, qualitative data are used in our analysis to illustrate the quantitative results. In April 2009, 15 qualitative interviews were carried out with individuals having responded to the event history and social network questionnaires. Using the sampling frame of the 'quantitative' survey on households, the sampling of respondents, whose interviews took place at the respondents' home and/or workplace, intended to include individuals with diverse characteristics regarding specifically their occupations, professional and migration experiences. The interviews were semi-structured, following the event history questionnaire, and a comprehensive interviewing guide in order to streamline the reporting and recording of the narratives. The emphasis was placed on the social network formation and dynamics of the interviewees, on the resources they had acquired over their life span (social capital, human capital and financial capital), on the help they had received at different stages of their trajectories (schooling, marriage, housing, job), and on the process of professional insertion and transitions. The duration of the interviews varied between 45 minutes and one hour and a half.

Defining and measuring socials network characteristics

The concept of social network is mainly addressed from two different perspectives. In the first one, which is dominant in the field of social network analysis, a social network is defined as a social structure made of finite set of nodes (which are generally individuals or organizations) that are tied by one or more specific types of interdependency, such as kinship, friendship, values, beliefs, conflict or trade. It is called 'whole network' or 'complete network'. Following this perspective, the structural aspect of networks is by itself sufficient to explain social outcomes (Degenne and Forsé 2004). The second approach, which prevails in the economics literature,

3 For more details, see Boyer and Delaunay (2009).
4 Weights are applied in all calculations to take into account the sampling scheme.

defines social network from an 'egocentered' standpoint as a set of human contacts known to an individual, by whom he/she expects to share material or intangible resources. What is called 'personal' or 'egocentered' network is thus composed of a focal individual, named 'Ego', a set of Ego's direct social contacts, named 'alters' and the ties between them. In this paper, we adopt this definition of social networks because it allows the exploration of personal relationships beyond pre-defined geographical, organizational or community boundaries (Berrou and Combarnous 2012).

The structure of social networks is considered in this paper but also the ties contents and the resources dimension. Most of them are measured with a name-generating methodology in the 'quantitative' survey (McCallister and Fischer 1978). More precisely, six name generators are used. We asked the respondents to provide a list of names of those who had helped them in various situations: throughout schooling[5], 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 their last job or to improve their current professional activity[6], and to find housing. In addition, the respondents were asked to cite all their siblings from the same mother and father who are currently alive, 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 strength of ties, and for knowing the socioeconomic statuses of those cited and thus the social resources they may provide. These name generators allow us to collect information on 14 696 alters.

[5] 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?".
[6] 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?".

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. Indeed, using the characteristics of the entire network at the time of the survey would be problematic given that this network may evolve over time, partly depending on the success or failure of the worker's professional career. This would not only be a problem of endogenous social network formation with regard to labour market outcomes, but would also amplify the temporality problem that we face with our survey because we observe the social network at different time: at the time of the workers' last employment change for contacts used for professional goals, during the past 12 months for financial support or at the time of the last move.

To limit endogeneity and timing problems, we essentially rely on information about the kinship. Using the kinship as a measure of social network is a way to tackle these difficulties, making the assumption that the size of the kinship is not subject to endogenous changes over the individuals' professional life. Indeed, it is recognized in the literature in economics that kinship ties with actual genealogical ties can be seen as largely exogenous and cannot be freely changed or only at a high psychological cost (La Ferrara 2007). In addition, some studies show that kinship ties are crucial for professional activity in the Sub-Saharan African context: at the start of an enterprise, but also to face a professional shock (Berrou and Combarnous 2012; Fafchamps 2002; Lourenço-Lindell 2002). In our survey, kinship ties represent 60 percent of all the support received to improve the current professional activity (Pasquier-Doumer 2010). Kinship may then be a good proxy of social network as far as transitions on the labour market are concerned.

We decide to restrict to siblings and not to use the extended family as a measure of the social network, such as cousins, uncles and aunts. This is because we do not capture the actual blood relationships of the respondents with other parents quite perfectly. This problem is worsened by the fact that many communities of migrants in West Africa call each other 'cousins' (for example the large Ivorian diaspora in Burkina Faso). Then, not being able to take into account true blood relationships may worsen the potential endogeneity of the link between social networks and labour market outcomes. Yet, an issue with the sibling size is the possible existence of differential mortality, i.e. diverging expectations of life for different age cohorts: older cohorts of workers may have lost more brothers and sisters than younger generations of workers at the same age. To check for this possible phenomenon in the size of the siblings, we account for age and use crossed age-siblings effects in the regressions to show to what extent this may affect our estimates.

Three types of social network variables are finally computed to characterize the network in its three main dimensions, i.e. structure, resources and strength of ties: (1) the total number of declared individuals in the network, which is not used directly in the regressions for reasons mentioned above; the number of siblings that aims at characterizing one dimension of the structure, the network size of Ego, also called the degree of a node (Jackson 2008); (2) the average and maximum years of schooling of the siblings and dummies taking value one if a member of the siblings has a job in the public sector, which is supposed to capture resources embedded in one's network[7]; (3) four variables aiming at reflecting the strength of ties, defined by Granovetter (1973, p.1361) as a *"combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie"*: an index of the geographical remoteness of the siblings to Ouagadougou[8], and the geographical distance from Ouagadougou to the worker's locality, village or province of origin[9], assuming that a longer distance makes it

[7] We also use a dummy taking value one if a member of the whole network has a job in the public sector, but we do not use it directly in the regression for reasons mentioned above.

[8] 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.

[9] 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

more difficult and costly to keep in touch with the family and the kin (an 'out of sight, out of mind' effect), hence that the intensity of the ties declines with distance (Gubert and Fafchamps 2007; Whitehouse 2011); the number of people that were helped by the respondent during the past year, and a dummy taking value one if the individual had at least one visit to his/her parents (or extended family) or to friends over the past week[10], which both aim at reflecting the reciprocal dimension of ties. However, the exogenous status of the latter two variables – number of people helped, and visit to parents and friends - may be questionable. The variable related to visits to parents or friends is potentially endogenous to changes in the employment status if these visits aimed at showing gratitude to parents or friends who supported Ego when the occupational change occurred. Yet, the time interval between the observation of the visits (one week before the survey) and the employment transition is very large (12 years on average), which makes us believe that this variable is not endogenous to previous labour market choices, as far as we assume that visits to show gratitude would decrease with time. Indeed, many other events have occurred that may have shaped the strength of the ties. To still limit the possible endogeneity, we exclude from the regressions the visits to friends and include only the visits to parents. We then consider the visit dummy as a structural measure of strength of kinship ties. The number of people helped by Ego is highly correlated to the current employment status and thus to previous employment transition. That is the reason why we do not use this variable directly in the regressions.

Regarding the use of the variable of geographical distance from Ouagadougou to the worker's locality, village or province of origin – which is deemed to reflect the intensity of the individuals' relationship with their kinship network, one could object that it may not affect transitions if such transitions precisely occurred before the workers arrived in Ouagadougou, so prior to their

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 in very different conditions.

[10] The survey includes an entire module that aims at measuring all the travels of the respondent during a week.

migration. We checked this possibility and found that employment transitions taking place outside Ouagadougou concerned only 5 percent of workers who experienced a transition, so that this argument does not invalidate the use of such distance variable. Another problem with the use of geographical distance could be that high ability workers may be more likely to move to urban areas and, even more problematically, may be willing to migrate further. In such case, distance may be correlated with unobserved characteristics of the workers and might just pick up the effect of abilities in the regressions. We deal with this issue by relying on 'frailty' models which consist of modeling the unobserved heterogeneity component thanks to the structure of the event history data (see Section 3).

Measuring 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, called 'failure' thereafter (see Section 3), are examined in this paper. The first one is the transition from unemployment to employment (1). The two other transitions can be described as changes in the worker's employment status: wage employment to self-employment (2), and self-employment to wage employment (3). Let us briefly describe how we defined the different employment changes.

For some individuals, there has been some time out of employment or of the labour market. Should this be included or not in the record of employment changes? Kambourov and Manovskii

(2008) argue that excluding career breaks would underestimate changes. However, the relationship between job changes and breaks in employment probably varies by gender, as the change of occupation for women 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.[11] 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[12] (see the distribution of event occurrences for men and women in Table 1). 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 changes in employment status, 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. 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

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[11] 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 employment 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 a very small probability of failure in many cases. The results of these exercises are not discussed in this paper for lack of space but are available from the authors upon request.

[12] See the hazard model presented in Section 3.

preceded by short withdrawals from activity, i.e. those transitions which were unavoidably broken up by frictional unemployment, i.e. 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).

Finally, we treat each respondent's job spell as a separate case for analysis, meaning that the observation unit is transitions or changes in employment status, not individuals.

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	786	322	12.2
Men	228	118	6.2
Women	558	204	15.6
(2) Wage employment to self-employment			
Overall	1250	181	9.9
Men	999	168	9.9
Women	251	13	8.8
(3) Self-employment to wage employment			
Overall	1347	130	12.2
Men	918	119	12.5
Women	429	11	9.1

Source: Ouaga2009 survey, authors' calculation.

Table 2 provides descriptive statistics of workers having known the three types of transitions. Looking at the first transition from unemployment to employment, two social network features diverge significantly between workers who experienced such a transition and those who did not experience it at the time of the survey ('failure' versus 'no failure', see the hazard model presented in Section 3), both related to network structure. Unemployed workers who experienced a transition to employment have a larger social network: they declare having on average 5.8

individuals in their network and 4.0 siblings, while unemployed workers who did not experience such transition declare respectively 3.9 individuals and 2.9 siblings. However, it is premature to conclude at this stage that social network capital fosters job access in the labour market.

If we then compare wage workers who evolve in this status with wage workers who transit to self-employment (Column (2)), we observe high differences between these two types of workers: wage workers without transition are on average younger, more educated and richer than wage workers who become self-employed. They work more often in the public sector (34 percent are in the public sector compared with 12 percent for those who become self-employed). They are endowed in a larger social network with higher resources. Lastly, they maintain weaker ties with their kinship, as measured by the distance to the birthplace. However, we do not know whether this last result is due to the existence of a selection effect of migration. In addition, most of wage workers having experienced a transition have become self-employed while they were already living in Ouagadougou. For the majority, the transition has not occurred because of the Structural Adjustment Program or the devaluation of the CFA francs in 1994.

Differences between self-employed workers who transit to wage employment and self-employed workers without transition are weaker. The former are older and more often migrant, although the transition occurred 11 years on average after migration to Ouagadougou. Self-employed workers who transit to wage employment have also a poorer network in terms of resources.

To conclude, we attempted to hierarchize the employment transitions. Due to data limitations, we cannot clearly infer a welfare gain for each transition, expect for the transition of unemployment to employment. However, using Ego's average level of education and average level of wealth, we can highlight general trend. Workers who evolve in wage employment are on top of the socio-economic ladder and benefit from a large social network with high resources. At the bottom of the socio-economic ladder are the self-employed workers who have become wage workers. They are also those with the narrower and less endowed in resources social network.

Self-employed workers without transition and wage workers who became self-employed fall between these two extremes, without clear distinction between the two.

Table 2. Characteristics of Workers by Transitions

Transitions	(1) Unemployment to employment			(2) Wage employment to self-employment			(3) Self-employment to wage employment		
Characteristics	No failure	Failure	Sig	No failure	Failure	Sig	No failure	Failure	Sig
Individual characteristics									
Average age	42.13	38.29		40.48	47.87	**	38.75	46.51	**
Dummy for Islam	0.61	0.64		0.47	0.54		0.65	0.55	
Dummy for Moore	0.84	0.75		0.74	0.91	**	0.88	0.87	
Dummy for born in Ouaga	0.21	0.35		0.22	0.23		0.29	0.14	**
Dummy for primary school or less	0.48	0.26	**	0.30	0.61	**	0.56	0.63	
Years of schooling	4.49	6.48	**	7.38	2.89	**	3.27	2.36	
Standard of living index in 2009	-0.19	0.09		0.18	-0.32	**	-0.35	-0.53	
Individual characteristics at failure time									
Potential experience (years)		8.97			15.15			17.00	
Dummy for living in Ouaga		0.92			0.81			0.84	
Time since arrival in Ouaga (years)		16.02			15.61			11.39	
Time since first child birth (years)		2.41			4.30			5.21	
Dummy for failure before the devaluation		0.27			0.56			0.45	
Activity characteristics before failure									
Dummy for wage-employment in public sector				0.34	0.12				
Dummy for self-employment in agriculture							0.17	0.51	
Social network characteristics									
Structure of the network									
Network size (N individuals)	3.87	5.78	**	5.31	4.48	**	4.71	4.68	
Number of siblings	2.86	4.04	**	3.73	3.07	**	3.32	3.06	
Resources embedded in the network									
Siblings'average years of schooling	4.18	4.68		5.05	2.07	**	2.87	1.62	**
Siblings'max years of schooling	6.17	6.88		7.74	3.47	**	4.44	2.53	**
Dummy for siblings in public sector	0.10	0.20		0.23	0.06	**	0.06	0.04	
Dummy for network members in public sector	0.17	0.28		0.32	0.10	**	0.12	0.07	
Strenght of ties									
Distance from the birthplace to Ouaga (hours)	2.65	3.35		3.58	2.36	**	2.71	2.45	
Dummy for the whole sibling in Ouaga	0.20	0.17		0.21	0.30		0.26	0.22	
Dummy for the whole sibling in Burkina but less than half in Ouaga	0.32	0.19		0.30	0.34		0.28	0.28	
Dummy for less than half of the siblings in Burkina	0.09	0.14		0.09	0.05		0.12	0.08	
Number of people helped by "Ego"	0.22	0.46		0.38	0.37		0.34	0.28	
Dummy for visit to parents	0.41	0.29		0.35	0.41		0.30	0.37	
Dummy for visit to friends	0.38	0.33		0.34	0.23		0.24	0.31	
Number of individuals	***105***	***112***		***702***	***162***		***738***	***113***	

Source: Ouaga2009 survey, authors' calculation. *Note:* in the columns "Sig.", ** means that the difference between "No failure" and "Failure" proportions is significant at the 5% level.

Some surveys 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 occupations and not the number of occupations for the workers. Let us clarify the possible consequence of this. If multi-activity were high among workers and if changes in employment status were higher in secondary jobs, then we would most probably underestimate the extent of changes in the considered population. Our numbers of labour market transitions should then be considered as lower bounds of the total number of transitions experienced by workers over their life time. However, from the Phase 1 of the *123 Survey* (Phase 1 is a Labour Force Survey) 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 (Hussmanns 2004). This means that we do not differentiate jobs 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 (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 different occupational statuses. 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 changes in employment status 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.

In addition, note that we use a professional experience variable as a regressor to mitigate this problem. This experience variable is not computed from the respondents' age, years of schooling, and age at school entry (as it is usually the case with potential experience), but makes use of the property of the event history data (Nordman and Roubaud 2009): 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.[13] This variable is one of the time-varying covariates in the hazard models presented in the next section.

3. Estimation strategy

The hazard models

To estimate labour market transitions and changes in employment status, 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

[13] As detailed work spells are available from the event history data, using an actual experience variable may also be an option, but it would be at the cost of adding a potential endogeneity issue between experience and labour market outcomes (see on this point Dustmann and Meghir 2005; Nordman and Roubaud 2009).

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).

The *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 covariates X yield similar estimates as long as the hazard rate is relatively "small" (Jenkins 2005).[14] 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 X 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 Ego's age in years, a dummy for being Muslim, another for belonging to the majority ethnic group (Moore), Ego's sibling birth-order, which is deemed to affect his schooling, health but also labour market outcomes (Behrman and Taubman 1986; Horton 1988), three dummies for his level of schooling (primary, lower secondary, higher secondary and above), and a standard of living index, which is supposed to partially control for Ego's social origin in terms of wealth, because of the very low level of social mobility observed in Burkina Faso (Pasquier-Doumer 2012). This index is calculated using multiple correspondence analysis on the basis of information on the ownership

[14] 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.

of durable goods, dwelling conditions, and access to utilities.[15] An additional control 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), the time elapsed since first child birth (equal to zero for individuals with no children), and a period dummy taking value one if the transition failure occurred prior to the devaluation of the CFA Francs in 1994. This latter variable is introduced as a control for conjuncture and policy measures effects following the Burkinabe's Structural Adjustment Program, which may have shaped labour market insertion and dynamics.

Finally, we introduce the vector of variables characterizing the individuals' social network at the time of the survey (*SN*). These variables are described in the data section and discussed using a principal component analysis, which is detailed below. The discrete-time hazard function (*cloglog* function) that we estimate for interval $(a_{j-1}, a_j]$ can be written as

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

In the model 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, ignoring unobserved heterogeneity may result in different biases (Jenkins 2005): first, non-frailty model may over-estimate the degree of negative

[15] The set of variables is the ownership of TV, radio, refrigerator, fan, bicycle, motorbike, car, computer, the ownership of housing, WC, own kitchen, in-house running water facility, *electricity*, composition of wall, house keeper, type of housing, street lighting and garbage collection. The index is built using the coordinates of the first axis, which is very discriminating in terms of standard of living.

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

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

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.

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[16], 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 also 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 as we do, 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 3 reports the main diagnostics of this PCA.[17] In this analysis, we do not restrain the list of social network variables related to siblings but we use the full set of social network variables described in the data section. This is because we want to keep a large view of the available social network information in order to be able to identify the most influential and/or meaningful social network variables in our data and also because endogeneity is not an issue at this step.

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

[17] 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.

Table 3. Principal component analysis (PCA) of social network characteristics

Factors	Eigenvalues	Difference	Proportion	Cumulative
Factor1	3.41672	0.81941	0.2441	0.2441
Factor2	2.59730	0.92425	0.1855	0.4296
Factor3	1.67305	0.48758	0.1195	0.5491
Factor4	1.18547	0.07126	0.0847	0.6338
Factor5	1.11421	0.10447	0.0796	0.7133
Factor6	1.00974	0.11025	0.0721	0.7855
Factor7	0.89949	0.11707	0.0642	0.8497
Factor8	0.78242	0.28760	0.0559	0.9056
Factor9	0.49482	0.19925	0.0353	0.9409
Factor10	0.29556	0.05942	0.0211	0.9621
Factor11	0.23614	0.05743	0.0169	0.9789
Factor12	0.17872	0.09820	0.0128	0.9917
Factor13	0.08051	0.04467	0.0058	0.9974
Factor14	0.03585	.	0.0026	1.0000

Source: Ouaga2009 survey, authors' calculation.

The pairwise correlation coefficients of the social network's and individual's main characteristics with the first six factors are then used for the interpretation of the computed factors (Table 4). The six factors are closely associated with the following characteristics: Factor 1 corresponds to the resources embedded in the networks, combining education and the activity portfolio of the network, in particular whether its members have a job in the public sector. Factor 2 is mainly summarized by the distance to the region or village of origin, as it is highly correlated to the two variables describing the costs (in CFA francs) and time (in hours) necessary to travel to the individual's locality of origin. This factor may be interpreted as the weakness of ties with the kinship as a whole. Factor 3 reflects the network size, i.e. the total number of declared individuals in the network and the number of siblings. Factor 4 is highly correlated to information summarizing the fragmentation of the siblings, i.e. whether siblings live in Ouagadougou and abroad. Its interpretation is very close to that of Factor 2, but with a restricted definition of kinship, i.e. the weakness of ties with the biological family. Factors 5 and 6 combine two dimensions of social network: the strength of ties and the resources embedded in the network. Factor 5 stresses strong ties, as it is positively correlated with the number of visits to friends (and to parents but to a lesser extent), and a high level of resources, captured by the educational level of the siblings and to a lesser extent by the activity portfolio of the network. Finally, Factor 6 reflects strong ties with few resources, as it is positively and highly correlated to the number of visits to parents the past week, and to the number of people that were helped by Ego. By contrast, this factor is negatively correlated to education of the siblings. It is worth noting that Factors 1, 5 and 6 highlight a well-known phenomenon of social network analysts which is called 'homophily' (McPherson et al. 2001). This pervasive phenomenon refers to a tendency of various types of individuals to associate with others who are similar to themselves. Here, low educated Egos are associated with networks that are poorly endowed in resources, and vice versa.

These six factors therefore reflect a wide range of social network characteristics. More importantly, we find that the factors are rather clearly defined and have all a relevant interpretation according to the literature. These network characteristics can mainly be described by the network's size/structure, network's resources (education, professional activity of its members), and strength of ties (geographical remoteness, fragmentation and reciprocity), as well as by a combination of these characteristics. Using these factors in regressions will then be a way to combine different dimensions of the individuals' social network, providing therefore a complement to regressions introducing social network variables directly.

Table 4. Pairwise correlation coefficients between PCA factors, social network and individual characteristics

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
	Resources embedded in the network	**Distance to the origin locality/ Weak ties with kinship**	**Size of the network**	**Fragmentation of the siblings /Weak ties with siblings**	**Strong ties, and high level of resources**	**Strong ties, and low level of resources**
Social network characteristics						
Network size	0.2070*	0.1780*	**0.8229***	0.0649*	0.1951*	0.1785*
N siblings	0.2499*	0.1291*	**0.9158***	-0.0266	0.2058*	-0.1701*
Siblings'average years of schooling	**0.7226***	0.3752*	0.3333*	-0.3382*	**0.6201***	**-0.5296***
Siblings'max years of schooling	**0.7387***	0.3870*	0.4746*	-0.3013*	**0.6222***	**-0.5008***
Siblings in public sector	**0.8868***	0.1608*	0.2353*	-0.0501	0.1228*	-0.0905*
Network members in public sector	**0.8574***	0.1639*	0.1485*	0.0063	0.0991*	0.0845*
Distance from the birth place to Ouaga (hours)	0.1660*	**0.9527***	0.0809*	0.3521*	0.0984*	0.0090
Distance from the birth place to Ouaga (CFA)	0.1855*	**0.9635***	0.1170*	0.3144*	0.1376*	-0.0202
Siblings' remoteness to Ouaga	0.0116	0.3002*	0.0386	**0.8940***	0.0492	0.0849*
N siblings in Ouaga	0.1919*	-0.1679*	0.6049*	**-0.6966***	0.1957*	-0.2360*
N siblings abroad	0.0377	0.4128*	0.3530*	**0.6492***	0.1833*	-0.1836*
N people helped by Ego	0.1152*	0.1236*	0.2199*	0.0045	0.0593	**0.6075***
Visit to parents	0.1106*	0.0793*	-0.0154	-0.0481	0.3448*	**0.5046***
Visit to friends	0.0498	0.0403	0.1123*	0.0034	**0.7804***	0.0411
Individual characteristics						
Aged 26-35 years	0.0559	0.0455	0.1497*	-0.0448	0.1046*	-0.0904*
Aged 45 years and more	-0.0946*	-0.0683*	-0.3044*	0.1153*	-0.1924*	0.1790*
Islam	-0.2124*	-0.0023	-0.0826*	0.0452	-0.1212*	0.0678*
Moore	-0.2251*	**-0.3879***	-0.0682*	-0.1539*	-0.1556*	0.0392
Born in Ouaga	0.0405	**-0.4570***	0.1260*	**-0.4508***	0.1739*	-0.2079*
Primary school	-0.0307	-0.0347	0.0727*	-0.1425*	0.0659*	-0.0356
Lower secondary school	0.1305*	0.0567	0.0726*	-0.1009*	0.1471*	-0.1401*
Higher secondary school and above	**0.4664***	0.3112*	0.2305*	-0.0188	**0.3144***	-0.1603*

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

4. Results

Table 5 reports a synthesis of these hazard model estimations. 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).

Table 5. 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	(4) Frailty model
Individual characteristics												
Muslim	0.221	0.268	0.314	0.363	0.0654	0.0488	0.0400	0.00516	-0.355	-0.335	-0.361	-0.335
	(0.237)	(0.243)	(0.267)	(0.242)	(0.199)	(0.198)	(0.206)	(0.215)	(0.219)	(0.219)	(0.234)	(0.243)
Moore	0.173	0.0421	0.184	0.0115	0.203	0.226	0.221	0.241	0.166	0.128	0.0585	0.00931
	(0.267)	(0.278)	(0.274)	(0.274)	(0.297)	(0.298)	(0.287)	(0.294)	(0.360)	(0.366)	(0.302)	(0.532)
Primary school	0.715**	0.709**	0.428	0.430	-0.00666	-0.0235	-0.0362	-0.0432	0.526*	0.534*	0.510*	0.505
	(0.330)	(0.328)	(0.358)	(0.348)	(0.251)	(0.253)	(0.267)	(0.277)	(0.276)	(0.277)	(0.301)	(0.314)
Lower secondary school	0.112	0.0768	-0.00431	-0.00749	-0.566	-0.568	-0.376	-0.372	0.735	0.735	1.113**	1.071**
	(0.420)	(0.411)	(0.458)	(0.443)	(0.397)	(0.400)	(0.397)	(0.402)	(0.462)	(0.466)	(0.462)	(0.472)
Higher secondary school & above	0.910**	0.928**	0.782	0.868*	-1.019**	-1.021**	-0.888**	-0.844*	0.953	0.966	1.529**	1.467**
	(0.422)	(0.416)	(0.511)	(0.491)	(0.414)	(0.415)	(0.422)	(0.432)	(0.614)	(0.614)	(0.622)	(0.636)
Potential experience (years)	0.0709**	0.0600**	0.0600***	0.0497**	0.0331	0.0308	0.0499**	0.0485**	0.0655**	0.0650**	0.0980***	0.0997**
	(0.0300)	(0.0296)	(0.0174)	(0.0213)	(0.0254)	(0.0254)	(0.0223)	(0.0243)	(0.0323)	(0.0322)	(0.0205)	(0.0451)
Potential experience squared	-0.003***	-0.002***	-0.002***	-0.002**	-0.00078	-0.00075	-0.00098*	-0.00098*	-0.0011	-0.0010	-0.0016***	-0.00155
	(0.00096)	(0.00093)	(0.00066)	(0.00072)	(0.000594)	(0.000591)	(0.000552)	(0.000560)	(0.000706)	(0.00070)	(0.000495)	(0.00097)
Time since arrival in Ouaga	0.0182	0.0192	0.0207	0.0203	0.0177**	0.0184**	0.0196**	0.0196**	-0.0145	-0.0133	-0.0171*	-0.0150
	(0.0141)	(0.0141)	(0.0135)	(0.0154)	(0.00892)	(0.00889)	(0.00869)	(0.00928)	(0.00942)	(0.00928)	(0.00983)	(0.0101)
Time since first child birth	-0.0302	-0.0267	-0.0333	-0.0308	-0.0609***	-0.058***	-0.0646***	-0.0617***	0.00560	0.00530	0.00825	0.00615
	(0.0287)	(0.0287)	(0.0261)	(0.0249)	(0.0220)	(0.0222)	(0.0220)	(0.0224)	(0.0260)	(0.0258)	(0.0245)	(0.0293)
Time since first child marriage	-0.00848	-0.0136	-0.0144	-0.0198	-0.0101	-0.0133	-0.00672	-0.0111	-0.0276	-0.0301	-0.0170	-0.0189
	(0.0219)	(0.0223)	(0.0175)	(0.0208)	(0.0214)	(0.0212)	(0.0219)	(0.0213)	(0.0238)	(0.0236)	(0.0230)	(0.0278)
Agricultural sector					1.346***	1.345***	1.329***	1.334***	1.173***	1.215***	1.246***	1.306***
					(0.226)	(0.226)	(0.254)	(0.256)	(0.242)	(0.242)	(0.260)	(0.264)
Standard of living index	0.175	0.146	0.116	0.0914	-0.0728	-0.0715	-0.0356	-0.0200	-0.0685	-0.103	-0.0977	-0.130
	(0.159)	(0.153)	(0.171)	(0.158)	(0.131)	(0.132)	(0.138)	(0.140)	(0.162)	(0.161)	(0.177)	(0.181)
Birth order	0.0309	-0.000621	-0.00582	-0.0308	0.0668	0.0502	0.0999	0.0770	-0.0294	-0.0597	-0.0781	-0.0980

	(0.105)	(0.1000)	(0.0962)	(0.110)	(0.0820)	(0.0787)	(0.0799)	(0.0805)	(0.0947)	(0.0902)	(0.0923)	(0.0944)
Age	-0.00164	0.00250	-0.0123	-0.00813	0.00961	0.0105	0.00465	0.00534	-0.00811	-0.00481	-0.0229***	-0.0216
	(0.0168)	(0.0167)	(0.00936)	(0.00770)	(0.0124)	(0.0124)	(0.00840)	(0.0109)	(0.0145)	(0.0147)	(0.00879)	(0.0138)
Devaluation dummy	0.0392	-0.0880	0.103	-0.0470	-0.304	-0.314	-0.490*	-0.511*	-0.0606	-0.0527	-0.189	-0.156
Social network characteristics	(0.341)	(0.339)	(0.278)	(0.269)	(0.290)	(0.291)	(0.262)	(0.288)	(0.327)	(0.326)	(0.301)	(0.334)
Siblings size	-0.0466		-0.0205		-0.0231		-0.0678		-0.00228		0.0104	
	(0.0633)		(0.0686)		(0.0567)		(0.0575)		(0.0656)		(0.0672)	
Siblings'average years of schooling	-0.0548*		-0.0514		-0.00164		0.00417		-0.0711*		-0.115**	
	(0.0330)		(0.0346)		(0.0297)		(0.0292)		(0.0420)		(0.0478)	
Siblings in public sector	0.298		0.449		-0.279		-0.553		0.461		0.670	
	(0.340)		(0.343)		(0.335)		(0.368)		(0.431)		(0.463)	
Distance from the birth place to Ouaga (hours)	0.0998*		0.0971*		0.0452		0.0389		0.0325		-0.0166	
	(0.0543)		(0.0503)		(0.0522)		(0.0509)		(0.0579)		(0.0620)	
Siblings' remoteness to Ouaga	0.142*		0.128*		-0.0710		-0.0757		0.0877		0.128*	
	(0.0746)		(0.0702)		(0.0757)		(0.0704)		(0.0789)		(0.0761)	
Visit to parents	-0.126		-0.106		0.0940		0.215		-0.0336		-0.215	
	(0.227)		(0.232)		(0.191)		(0.203)		(0.234)		(0.264)	
Factor 1		-0.00135		0.0458		-0.0910		-0.169		-0.0984		-0.117
Resources embedded in the network		(0.112)		(0.111)		(0.125)		(0.139)		(0.169)		(0.188)
Factor 2		0.154		0.148		0.156		0.173		0.0429		-0.0799
Distance to the origin locality/Weak ties with kinship		(0.136)		(0.124)		(0.133)		(0.142)		(0.146)		(0.172)
Factor 3		-0.00253		0.0666		-0.0151		-0.131		0.204		0.228*
Size of the network		(0.118)		(0.121)		(0.109)		(0.122)		(0.129)		(0.141)
Factor 4		0.262**		0.218*		-0.168		-0.288**		0.193		0.276**
Fragmentation of the siblings/Weak ties with siblings		(0.116)		(0.123)		(0.128)		(0.144)		(0.126)		(0.137)
Factor 5		-0.166		-0.219*		-0.0650		-0.0678		-0.169		-0.310*
Strong ties and high level of resources		(0.128)		(0.132)		(0.109)		(0.119)		(0.143)		(0.164)
Factor 6		0.203*		0.216**		0.153*		0.218**		0.148		0.106
Strong ties and low level of resources		(0.105)		(0.106)		(0.0958)		(0.105)		(0.106)		(0.120)
Constant	-3.813***	-3.297***	-3.454***	-2.837***	-4.943***	-5.165***	-4.955***	-5.345***	-5.492***	-5.427***	-5.229***	-5.311***
	(0.800)	(0.686)	(0.300)	(0.333)	(0.775)	(0.656)	(0.461)	(0.533)	(0.904)	(0.756)	(0.461)	(0.736)
ln_varg			-14.24	-14.37			-14.00	-13.97			-13.36	-13.33
			(457.5)	(425.4)			(484.3)	(471.1)			(401.3)	(465.2)
Observations	1324	1324	1324	1324	10544	10544	10544	10544	10726	10726	10726	10726

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

Transition from unemployment to employment

Looking at the non-frailty Model 1, three characteristics of the network seem to influence (at the 10 percent level) the propensity to find a job when individuals are unemployed: the average education of the siblings, with a negative effect; the distance to the area of origin, with a positive sign; and the siblings' remoteness to Ouagadougou, again with a positive sign. By taking into account the individuals' unobserved heterogeneity in Model 3, we refine these estimates, and the effect of the siblings' education vanishes.

The two remaining significant and robust effects of geographical location (distance to origin locality and remoteness of the siblings) have an interesting interpretation in this context of access to employment. They suggest that a longer distance between the unemployed and his/her kin in the village of origin may lead to higher motivation to find a job. This may happen for a least two reasons. First, the longer the distance to the kin who stays in the locality of origin, the less efficient the safety net in case of unemployment. Thus, migrants to the capital who find themselves far from their origin locality might be even more motivated to find a job, and may accept job offers faster than migrants who left a closer locality where it is easier to find support from their family in case of financial difficulties. *Rasmané*'s life history (Interview 6) highlights the difficulty to survive far from his family. When *Rasmané,* a tailor of 45 years old, migrated to Ouagadougou, he was 14 years old and did not know anybody in Ouagadougou except a distant friend of his father, with whom the father made business of kola nuts. His parents sent him to Ouagadougou with the hope that he will learn a trade. Unlike the other children of the father's friend, he was undernourished and had to work hard to contribute to the expenses of the household. This leads him to say: "*In Africa, when you do not have your family nearby, you should know that you will suffer*". *Balkissa* (Interview 1), a 41 years old unemployed widow, also illustrates the difficulty to live far from her family. She had to leave the family neighbourhood in Ouagadougou when her husband died to join a cheaper and suburban district. The head of her family, her father's brother, gives her some help, but only when she visits him. Because she is poor, it is very difficult for her to cross the city to visit them.

A second interpretation calls for the possible disincentive effect exerted by the kinship network in terms of 'earnings predation'. Such adverse incentive effects could arise if migrants feel that everything they earn needs to be shared with the kin and extended family, or that labour incomes may even attract family members with whom these earnings have to be shared.[18] Demands from the kin or more broadly from people in the village of origin may then have a disincentive effect on the job search and this effect gets diluted with geographical distance. Indeed, the longer the distance to the kinship network, the higher the costs for the kin to observe the labour earnings of the worker.[19] As an illustration, *François*, together with his wife *Denise* (Interview 2), both self-employed as tiler and weaver respectively, explains that he keeps close ties with his family that lives in a village 15 kilometers away from Ouagadougou. They both pay regular visits to the parents of *François*, three or four visits from the beginning of 2009 (the survey took place in April), and they also receive regular visits from sisters and brothers at various occasions (marriages or funerals). They receive presents from the village, but they both have the feeling that they "*give more than they receive*". This is because the members of the family of *François* are worse off than they are. In the same vein, *Inoussa* (Interview 13), 29 years old, an apprentice in a store of furnitures, has migrated to Ouagadougou when he was 18 years old, from a village 18 kilometers away, where his family still resides. He explains that he has many friends from the village who

18 The idea that family and kinship ties may imply adverse incentive effects is relatively old. It is quite often mentioned in the anthropological literature, was emphasized by modernization theorists, and was developed in the field of economic sociology and social network analysis as the downside of strong ties. More recently, this question has been taken up by economists (see e.g. Platteau, 2000; Hoff and Sen, 2006; Luke and Munshi, 2006; Grimm et al., 2013).

19 For entrepreneurs in West Africa, including in Ouagadougou, Grimm et al. (2013) provide evidence that family ties can be source of pressure to redistribution that prevent their economic development. Analyzing the resource allocation and value added of informal entrepreneurs in seven West African capitals, the authors find robust negative effects associated with social ties in the village of origin and observe that these effects decrease with geographical distance.

come to Ouagadougou and visit him. They are often hosted by *Inoussa* for several days. As he says, "*In Africa, if you know somebody and you don't know his place, it is as if you actually don't know him*".

We then refine these estimates by looking at the other set of regressions which replace the social network characteristics introduced in levels by the six computed factors stemming from the principal component analysis (Models 2 and 4, non-frailty and frailty respectively). As mentioned in Section 3, this procedure has the advantage of introducing regressors which are, by definition, orthogonal to each other, therefore circumventing potential multicollinearity issues among social network variables. In addition, in so doing, we intend to test the effect of combined dimensions of the individuals' social network, providing therefore a complement to previous estimates. Finally, as shown before, the six factors have a rather clear interpretation which may clarify the meaning of our econometric results.

From our (preferred) frailty Model 4, we find that Factors 4 and 6 exert a positive and significant effect on the probability of escaping from unemployment. We thus confirm the previous positive effect of the fragmentation of the siblings (Factor 4). The novelty here comes from the effect of Factor 6, which reflects strong ties with few resources (help given, the number of visits to parents together with having poorly educated siblings). Workers with strong ties, providing help to others, and with poorly educated siblings obtained a job faster. The possible interpretation of this positive effect calls for a timing issue: these workers are probably rewarding at the time of the survey the support they had received in the past when they were unemployed, first from their close family (by the number of visits paid to parents), but also from their friends (by the number of people helped by Ego).

Finally, the negative coefficient associated with Factor 5 is not at odds with previous findings. Indeed, Factor 5 emphasizes the capacity of a network to provide support, by combining strong ties with high level of resources. Workers with this type of networks spend more time unemployed, all else being equal. This might be a reflection of 'luxury unemployment', as it is easier to stay unemployed with a strong social support nearby.

To test the effect of time offset, in particular in the interpretation of Factor 6, we introduce interactions between Ego's age at the transition time and social network variables in Models 3 and 4.[20] We find that the dummy 'visit to parents' becomes significant with a negative sign and that its interaction with age is significant with a positive sign (Model 3 with interactions). This result confirms the existence of time offset: visits to parents may aim to support younger unemployed workers and to provide them with a safety net, which would discourage them to find a job; by contrast, older workers would visit their parents to express their gratitude for the support they had received in the past when they were unemployed. The positive and significant effect of the interaction of age with Factor 6 (Model 4 with interactions) is also in line with this interpretation.

Thus, we find that the social network, and even more the strong ties, does not necessarily help the unemployed find a job in the context of Ouagadougou. On the contrary, it may exert a disincentive effect, through the provision of a safety net or a pressure to redistribute, that leads unemployed to limit their effort to seek for 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 different forms of distortion on the labour market and where there is no unemployment insurance.

Transition from wage employment to self-employment

As shown in Table 5 and Table 6, social network variables have no effect on the propensity to experience a transition from wage employment to self-employment, when non-frailty models are

[20] Results of the estimation of the frailty model with interactions between age and social network variables are not shown to save space but can be obtained from the authors upon request.

considered (Models 1 and 2). But this result does not hold anymore if we control for unobserved individual effects (Models 3 and 4). As frailty models mitigate time-invariant unobserved heterogeneity bias, we limit our interpretation to these models.

The fragmentation of the siblings approximating the weakness of ties with siblings has a negative and significant effect, but only with the specification using factors: for wage workers, having weak ties with the siblings decreases the propensity to become self-employed. In addition, Factor 6, reflecting the combination of strong ties, in particular with kinship, and weak resources, has a positive and significant effect on the propensity to experience such a transition. By contrast, social networks with high level of resources seem to encourage wage-earners to pursue their career as wage-earners. Indeed, although non-significant, most variables approximating social resources of the network have a negative effect on the probability to transit from wage-employment to self-employment (for instance, siblings in the public sector, Factors 1 and 5).

Looking at the same Model 4 but adding age-interacted effects with the social network proxies allows us to refine these findings by taking into account the possible existence of differential mortality and migration timing of the siblings for different age cohorts (see discussion in Section 2).[21] It is indeed likely that the fragmentation of the siblings (interpreted here as a weakness of the ties) diverges across workers due to the presence of workers belonging to different age cohorts in the sample (so with possible differential mortality and migration), a fragmentation thereby reflecting genuine time effects, and not necessarily an erosion of the kinship ties. We find that the age interaction with Factor 4 has a significant coefficient at the 1 percent level with a negative sign, while the coefficient on Factor 4 (introduced in level) appears significant but with a positive sign. Hence, on average and for 'older' workers, having remote siblings is detrimental to transition to self-employment: it seems difficult and risky to make such professional change without strong kinship support nearby. For 'younger' worker, we do not observe this effect, on

[21] These results are not shown but available upon request.

the contrary. This result may be due to the fact that Factor 4 does not approximate well the weakness of siblings' ties for 'younger' worker. Indeed, Factor 4 may also reflect a selection effect to migration: those who left their brothers and sisters early to migrate far away from home are potentially more resourceful and able to operate a job transition to self-employment successfully. In addition, for young workers, having remote siblings may signify differential timing of migration among siblings. *Ousmane* (Interview 8) offers an illustration of this: at age 20, he decided to leave his family of farmers to "*seek his own destiny*" and "*to try his luck in Ouagadougou*". He was the first one of the siblings to make this decision, without his parents' agreement but, gradually, his siblings joined him in Ouagadougou.

The interaction of Factor 6 with age is also worth interpreting: its coefficient is positive and significant at the 5 percent level, while the effect of Factor 6 in level appears insignificant. Thus, the combination of strong kinship ties with weak resources has a positive and significant effect on the propensity to experience a transition from wage to self-employment, but this effect is relevant for 'older' workers only, i.e. not for those workers being at the early stage of their professional career.

The fact that strong kinship ties increase with time the probability to switch from wage-employment to self-employment, and even so when kinship ties are poorly endowed in resources, highlights both the importance of kinship for starting a business and the precariousness of self-employment, in particular for 'older' workers who transit from wage- to self-employment. The hazardous and precarious aspect of self-employment is confirmed by the negative and significant effects of having children[22] and of high level of education on the transition to self-employment.

François' transition (Interview 2) illustrates this result. When he dropped out of school, *François* worked as unpaid worker in the family farm for eight years. He decided to migrate to

[22] More precisely, we measure the effect of the time elapsed since the birth of the first child. The longer this time spell, the higher the probability to have other children.

Ouagadougou to join his siblings and found a job as domestic. When he lost this job six months later, his brother gave him 10 000 FCFA to buy a 'board' and to become street vendor. *Denise*, his wife, experienced a similar transition: after losing her job as hairdresser, she became self-employed weaver thanks to a familial informal loan of 22 500 FCFA, which allowed her to buy a loom. As already mentioned, *Denise* and *François* keep up very close ties with their family through frequent visits and gifts since they arrived in Ouagadougou.

These findings are along the same line as those of Barr (2002), who finds that entrepreneurs with smaller enterprises tend to maintain solidarity networks that are small, homogeneous, cohesive and best suited to reducing information asymmetries and thus supporting informal credit and risk-sharing arrangements.

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 Table 5 and Table 6): the size of the network has a positive and significant effect, when it is measured by Factor 3; the weakness of siblings ties, represented by Factor 4, has a positive effect as well; on the contrary, the resources of the network, captured by the average education level of the siblings, have a negative and significant effect on this propensity (Model 3). This is confirmed by Model 4 where the negative coefficient on Factor 5 means that a high level of resources embedded in the network combined with strong non-kinship ties are associated with a longer duration in self-employment.

Looking at the coefficients on other individual characteristics in Table 5, 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, in particular in the frailty specification (3), positive in the first case, negative in the second. More educated have higher propensity to transit because of selection into migration, as illustrated by the work history of *Boukaré* (Interview 9), a building custodian of 34 years old, who was a self-employed farmer and was selected by his family to migrate to Ouagadougou because he was the most educated of the family.

Thus, a larger network increases the probability to find a wage employment, most likely through better access to information. In addition, the weaker the siblings' ties, the wider the information received. This result suggests that workers without strong sibling's ties are encouraged to make more effort to socialize as they cannot find emotional support from their siblings. For instance, *Frederick* (Interview 5), a 29 years old man resuming his studies at the time of the survey, whose older brother lives in another city (Koudougou), spends a lot of time in his 'grin', an informal association of individuals of the same generation, living generally in the same neighborhood, and who meet up each other in the street to drink tea, chat and play cards. Kieffer (2006) defines the 'grin' in Ouagadougou as a place where individuals are engaged in reciprocal relationships, especially with the "*big brothers*" who play a protective role, are solicited for occupational projects, offer job opportunities and receive services in exchange. This 'grin' is for Frederick an essential source of information, which allows him to obtain various professional contacts and jobs opportunities. Through his 'grin', he found a wage employment as enumerator for an international NGO. He also developed a network of truck rental companies and he met a logistician to discuss the opportunity of this career path that he aims for.

These results seem to confirm Granovetter's predictions on the strength of the weak ties: larger networks with weak ties allow self-employed workers to get a better access to information on wage employment opportunities. Introducing resources dimension however changes the perception of the role of social network in the transition from self-employment to wage employment. Indeed, social networks endowed in high resources seem to discourage wage-workers to become wage-worker. Adding that wage employment found through the social network after a self-employed activity may be of poor quality, as discussed by the descriptive analysis (Table 2) and confirmed by our qualitative interviews, weak ties then enhance access to information on jobs but this information seems of little value.

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). Analysis of the qualitative interviews also illustrates the role of the resources of social network and the strength of non-kinship ties to experience upward mobility inside self-employment status. *Awa* (Interview 10), a 37 years old highly educated woman born in Bamako (Mali), who has migrated following her husband, explains the success of her textile trade by the help of friends and those of her husband to create a clientele, but also to invest in her activity. According to her, "*friends are more able to understand money issues*", supposedly than the family.

Crossed effects with age refine these findings: the size of the network (Factor 3) has still a strong positive and significant effect on transition from self- to wage employment, but its positive effect diminishes slightly with workers' age. In the same vein, the positive effect of the weakness of siblings ties (Factor 4) is also confirmed, and again with a decreasing marginal effect with workers' age. These two refinements may be due to the problem already mentioned of differential mortality of the siblings, but also to the time delay between the transition moment and the period at which we observe the siblings size (see Section 2).

In addition, a reversal of sign occurs across workers' age concerning the effect of the resources embedded in the network: for 'older' self-employed workers, Factor 5 has a negative effect on the probability to transit to wage-employment, but the reverse effect dominates for 'younger' workers (on average, i.e. over the entire sample, the sign is still negative as shown in Table 6). This finding may be explained by the characteristic of such transition: as discussed in the descriptive statistics when attempting to hierarchize the job transitions, self-employed workers changing for wage jobs may generally be associated with downward mobility in terms of job quality, often obtaining rather poor working condition wage jobs. But this might not be the case regarding the transitions of 'younger' self-employed workers, who are more likely to queue for high quality wage jobs because their opportunity costs may be greater. For such a transition to occur, high quality resources embedded in their networks are thus essential, but this effect does not dominate for the entire sample.

Table 6. Synthesis of hazard models estimations

Transitions	Unemployed 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 size	0	0	0	0	0	0
Siblings'average years of schooling	-	0	0	0	-	-
Siblings in public sector	0	0	0	0	0	0
Distance from the birth place to Ouaga (hours)	+	+	0	0	0	0
Siblings' remoteness to Ouaga	+	+	0	0	0	+
Visit to parents	0	0	0	0	0	0
Factor 1 (Network resources)	0	0	0	0	0	0
Factor 2 (Distance to the birth place/Weak ties with kinship)	0	0	0	0	0	0
Factor 3 (Network size)	0	0	0	0	0	+
Factor 4 (Fragmentation/ Weak ties with siblings)	+	+	0	-	0	+
Factor 5 (Strong ties and high level of resources)	0	-	0	0	0	-
Factor 6 (Strong ties and low level of resources)	+	+	+	+	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 workers on the labour market of a West African country. The main issue tackled 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 the resources embedded in the network from its structure and the strength of the ties. 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 the workers' social networks. In addition, we conducted qualitative interviews of a sub-sample of the workers having responded to the event history survey. To estimate labour market transitions and changes in the workers' employment status, we rely on a survival analysis that makes use of proportional hazard models for discrete-time data.

We find that social networks have a significant effect on the transitions of individuals on the labour market. However, this effect differs depending on the type of transition and on the dimension of the social network considered, i.e. the network size, the resources available in the network, and the strength of ties.

The network size appears to not matter much in the labour market dynamics, in particular in access to employment. The network size only plays a role in the transition from self-employment to wage employment, knowing that this transition is on average the most precarious. In this case, the network size seems to have an informative function, by conveying information throughout the network, but the information provided may be of little value. Network size is far from being the most important dimension of social networks in the transition from unemployment to employment. This is an important finding with regard to the existing literature, which mostly focuses on developed countries and highlights the efficient role of network size in job search. One of the reasons why this contradiction may exist is that the safety net function of the social network could dominate its informative function in a context where there is no formal safety net for unemployed workers.

Regarding the strength of ties, strong ties seem to play a stabilizing role in labour market dynamics. Indeed, having a network endowed in strong ties, in particular kinship ties, increases the probability to remain in the same status of activity for self-employed and unemployed workers. Strong ties seem to be of little use for access to wage employment. During the job search, unemployed workers having strong ties in their networks may tend to limit their effort to find a job. These results suggest that the safety net function of strong ties dominates their informative function. By contrast, weak ties are useful for self-employed workers to get a better access to information on wage employment opportunities or to be recommended, but without any guarantee with regard to job quality. Strong ties facilitate transitions in only one case, the transition from wage employment to self-employment. They play an important role for self-employed workers at every stage of their career, in particular at the start-up of a business but also later on. Strong ties may help self-employed workers face uncertainty or invest in a small business, but as they go hand in hand with homophily, they do not seem to help get away from a precarious status in the labour market.

In the same way, resources embedded in the network are a factor of occupational immobility: they have a negative effect on occupational transitions and this effect is reinforced when resources are combined with strong ties. The higher the network resources are, the more profitable it is to evolve within the self-employment or wage employment, and the weaker is the incentive it is to find a job.

Finally, what this study actually points out is that social networks have to be addressed taking into account their three explored dimensions and interactions. If not, the effect of social networks on labour market dynamics and labour market outcomes may well be misunderstood, in particular if network size is solely considered. This paper advocates the development of theoretical approaches that would take into account the coexistence of both the informative and safety net functions of social networks, which is particularly essential in a developing country context.

Another fruitful research agenda would be to deepen the understanding of social networks as factors of social immobility. However, data scarcity on the formation and development of social networks in developing countries is a concern as, ideally, what one would like to observe is the dynamics of personal networks across generations.

References

Barr, Abigail M. 2002. "The Functional Diversity and Spillover Effects of Social Capital." *Journal of African Economies* 11 (1):90-113.

Bentolila, Samuel, Claudio Michelacci, and Javier Suarez. 2010. "Social Contacts and Occupational Choice." *Economica* 77: 20-45.

Behrman, Jere R., and Paul Taubman. 1986. "Birth Order, Schooling, and Earnings." *Journal of Labor Economics* 4(3):121-50.

Berrou, Jean-Philippe, and François Combarnous. 2012. "The Personal Networks of Entrepreneurs in an Informal African Urban Economy: Does the 'Strength of Ties' Matter?." *Review of Social Economy* 70(1):1-30.

Bocquier, Philippe, Christophe J. Nordman, and Aude Vescovo. 2010. "Employment Vulnerability and Earnings in Urban West Africa." *World Development* 38(9):1297-1314.

Boyer, Florence, and Daniel Delaunay. 2009. "Ouaga 2009, Peuplement de Ouagadougou et Développement urbain." Unpublished manuscript, Institut de Recherche pour le Développement.

Bramoullé, Yann, and Gilles Saint-Paul. 2010. "Social Networks and Labor Market Transitions." *Labour Economics* 17:188-195.

Calvó-Armengol, Antoni, and Matthew O. Jackson. 2004. "The Effect of Social Networks on Employment and Inequality." *American Economic Review* 94(3):426-454.

Calvó-Armengol, Antoni, and Matthew O. Jackson. 2007. "Networks in Labor Markets: Wage and Employment Dynamics and Inequality." *Journal of Economic Theory* 132:27-46.

Degenne, Alain., and Michel Forsé. 2004. *Les réseaux sociaux*, 2nd ed. Paris: Armand Colin.

DIAL. 2007. "Youth and Labour Markets in Africa: A Critical Review of Literature." Working paper, DIAL DT 2007/02.

Dickerson, Andrew, and Francis Green. 2004. "The Growth and Valuation of Computing and Other Generic Skills." *Oxford Economic Papers* 56 (3):371-406.

Durlauf, Steven N., and Marcel Fafchamps. 2005. "Social Capital." In : *Handbook of Economic Growth*, ed. Aghion Philippe. and Steven N. Durlauf. ed1, vol 1(26):1639-1699.

Dustmann, Christian, and Costas Meghir. 2005. "Wages, Experience and Seniority." *Review of Economic Studies* 72(1): 77–108.

Fafchamps, Marcel. 2002. "Returns to Social Network Capital Among Traders." *Oxford Economic Papers* 54(2):173-206.

Fernandez, Rosa M., and Christophe J. Nordman. 2009. "Are There Pecuniary Compensations for Working Conditions? ." *Labour Economics* 16(2):194–207.

Fields, Gary. S. 2004. "A Guide to Multisector Labor Market Models." Paper presented at the World Bank Labor Market Conference, Washington, DC November 18-19.

Granovetter, Mark S. 1973. "The Strength of Weak Ties." *American Journal of Sociology*78:1360-80.

Granovetter, Mark S. 1995. *Getting a Job: A Study of Contacts and Careers*, 2nd ed. Chicago: Chicago University Press.

Grimm, Michael, Flore Gubert, Ousmane Koriko, Jan Lay, and Christophe J. Nordman. 2013. "Kinship-ties and Entrepreneurship in Western Africa", *Journal of Small Business and Entrepreneurship* 26: 125-150.

Gubert, Flore, and Marcel Fafchamps. 2007. "The Formation of Risk Sharing Networks." *Journal of Development Economics* 83(2):326-350.

Hoang, Ha, and Bostjan Antoncic. 2003. "Network-based Research in Entrepreneurship: A Critical Review." *Journal of Business Venturing* 18(2):165-187.

Hoff, Karla, and Amartya Sen. 2006. "The Kin as a Poverty Trap." In *Poverty Traps*, ed. Samuel Bowles, Steven N. Durlauf, and Karla Hoff. New York: Princeton University Press.

Horton, Sue. 1988. "Birth Order and Child Nutritional Status: Evidence from the Philippines." *Economic Development and Cultural Change* 36(2):341-354.

Hussmanns, Ralf. 2004. *Defining and Measuring Informal Employment.* Geneva: International Labor Office, Bureau of Statistics.

Ioannides, Yannis .M., Linda D. Loury. 2004. "Job Information Networks, Neighborhood Effects, and Inequality." *Journal of Economic Literature* 42(4):1056-1093.

Jackson, M. 2008. *Social and Economic Networks*. Princeton: Princeton University Press.

Jellal, Mohamed, Christophe J. Nordman, and François-Charles Wolff. 2008. "Evidence on the Glass Ceiling Effect in France Using Matched Worker-Firm Data." *Applied Economics* 40(24):3233–3250.

Jenkins, Stephen P. 2005. *Survival Analysis*, Unpublished manuscript, Institute for Social and Economic Research, University of Essex, Colchester, UK.

Kambourov, Gueorgui, and Iourii Manovskii. 2008. "Rising Occupational and Industry Mobility in the United States: 1968–97." *International Economic Review* 49(1):41–79.

Kieffer, Julien. 2006. "Les jeunes des « grins » de thé et la campagne électorale à Ouagadougou." *Politique Africaine* 101:63-82.

La Ferrara, Eliana. 2007. Family and Kinship ties in Development: An Economist's Perspective. Paper presented at the 5th AFD-EUDN Conference, Paris, December.

Lancaster, Tony. 1990. *The Econometric Analysis of Transition Data*, Cambridge: Cambridge University Press.

Lin, Nan. 1990. "Social Resources and Social Mobility: A Structural Theory of Status Attainment." In *Social Mobility and Social Structure*, ed. Breiger R.L. New York: Cambridge University Press.

Lourenço-Lindell, Ilda. 2002. *Walking the Tight Rope: Informal Livelihoods and Social Networks in a West African City*, Stockholm: Stockholm Studies in Human Geography 9, Almquist and Wiksell International.

Meagher, Kate. 2006. "Social Capital, Social Liabilities, and Political Capital: Social Networks and Informal Manufacturing in Nigeria." *African Affairs* 105(421):553-582.

McCallister, Lynne, and Claude Fischer. 1978. "A Procedure for Surveying Personal Networks." *Sociological Methods and Research* 7:131–148.

McKeever, Matthew. 2006. "Fall Back or Spring Forward? Labor Market Transitions and the Informal Economy in South Africa." *Research in Social Stratification and Mobility* 24:73–87.

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook. 2001. "Birds of a Feather: Homophily in Social Networks." *Annual Review of Sociology* 27:415–44.

Nordman, Christophe J., and François Roubaud. 2009. "Reassessing the Gender Wage Gap in Madagascar: Does Labor Force Attachment Really Matter?." *Economic Development and Cultural Change* 57(4):785-808.

Pasquier-Doumer, Laure. 2010. "Le rôle du réseau social dans les parcours de vie des Ouagalais." In *Peuplement de Ouagadougou et développement urbain*, ed. F. Boyer and D. Delaunay, IRD.

Pasquier-Doumer, Laure. 2012. "Inequality of Opportunity in the Urban Labor Market in West Africa." *Revue d'Economie du Développement* 26(2):44-66.

Parrado, Eric, Asena Caner, and Edward N. Wolff. 2007. "Occupational and Industrial Mobility in the United States." *Labour Economics* 14:435–455.

Platteau, Jean-Philippe. 2000. *Institutions, Social Norms and Economic Development.* Amsterdam: Harwood Academic Publishers.

Poulain, Michel, Benoît Riandey, and Jean-Marie Firdion. 1992. "Data From a Life History Survey and from the Belgian Population Register: A Comparison." *Population: An English Selection* 4:77-96.

Whitehouse, Bruce. 2011. "Enterprising Strangers: Social Capital and Social Liability Among African Migrant Traders." *International Journal of Social Inquiry* 4(1):93-111.