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Transitions in a West African labour market: The role of family networks

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ABSTRACT

This paper sheds light on the role of family 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 family networks on these transitions: their structure, the strength of their ties, and the resources embedded in them. 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 family networks, we estimate proportional hazard models for discrete-time data. We find that family 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 dimension of the family network considered. Network size appears not to matter much in labour market dynamics. However, strong ties play a stabilizing role by limiting large transitions. Their negative effect on transitions is reinforced by a high level of resources embedded in the network.

1. Introduction

A recent economic literature has emphasized the importance 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 markets, 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 faced regarding market opportunities, the reliance on partners, or the productivity of their prospective employees, and also to promote risk-sharing and informal credit arrangements (Hoang and Antoncic, 2003). Within the social network, family ties have been shown to play a key role in labour market outcomes (Granovetter, 1995), by enforcing informal agreements (La Ferrara, 2007). It has also been shown recently that recent graduates benefit from the use of family ties (parents) through a faster access to jobs and by better labour market outcomes (Kramarz and Skans, 2013).

These issues are decisive in developing countries where a large part of the inefficiency in the labour market may be due to imperfect information. These countries are often characterized by formal institutions which fail to channel information about jobs or market opportunities. In Ouagadougou (Burkina Faso) for example, 85% of unemployed workers are not registered in the public employment office and 45% declare that this is because they do not know it exists (DIAL, 2007). In the absence of formal institutions, the role played by interpersonal relationships and by family networks in particular may be substantial in employment trajectories.

While there is strong evidence of the importance of social and family networks in labour markets in developing countries, little is known in these countries about the specific effect of the different dimensions of these networks. Indeed, most studies in developing countries, particularly in Sub-Saharan Africa, focus on the size of 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 has been widely acknowledged that the intensity of ties is an essential dimension of social networks. Granovetter put forth 'the strength of weak ties' argument highlighting that links with infrequent interactions or with low intimacy, in other words weak ties, tend to bridge individuals across social groups, and are consequently the most informative and useful in the labour market. Following Granovetter's definition of the strength of ties, strong

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as well as weak ties can be observed even among family members. 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 network resources and tie content on the labour market. Besides, they mostly focus on business outcomes (such as Barr, 2002) and they do not address the issue of the dynamics of employment. An interesting exception is Kramarz and Skans (2013) who use a Swedish linked employer–employee dataset to show that strong social ties (parents) are an important determinant of where young workers find their first job but also of how they progress in their careers. For Africa, using a longitudinal dataset on young South Africans to examine the correlation of children's employment with parents' usefulness in job search, Magruder (2010) finds that fathers serve as useful network connections for their sons (but not daughters), contrary to mothers. Relying on an original dataset collected in the informal economy of Bobo-Dioulasso (Burkina Faso), Berrou and Combarnous (2012) argue that informal entrepreneurs have to combine strong and wide ongoing social support ties with weaker business ties to be successful. In the West African context again, Pasquier-Doumer (2013) has shown that informal entrepreneurs who have family members involved in the same activity perform better.

Other studies 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) finds 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, discounts, employment, and short-term loans or outright grants. For informal entrepreneurs in West Africa, including in Ouagadougou, Grimm et al. (2013) provide evidence that while family and kinship ties within the city tend to increase labour effort and the use of physical capital, distant kinship ties can be a source of pressure to redistribute which prevents these entrepreneurs' economic success.

Hence, family networks may affect the dynamics of workers in different ways and there is no clear evidence on what the main channel is. This lack of consensus may be explained by the low level of representativeness of data in Africa, but also because most studies fail to overcome the simultaneity issue between network constitution and the dynamics of workers.[1] Another difficulty is determining which features of the networks interact most with workers' trajectories, and through which channel, which requires detailed characteristics for these family networks.

In a West African context, this paper aims at disentangling the determinants of changes in workers' employment status and transitions from unemployment to employment by emphasizing the role played by family networks in stabilizing or helping workers improve their professional situation. A crucial question tackled is to what extent this is the case, and why different sorts of family networks may lead to different employment trajectories. We analyse the effect of family networks on specific employment transitions in Ouagadougou by answering the following questions. Do family ties help unemployed individuals have access to employment? To what extent is one's personal family network essential in the transition from wage employment to self-employment, or from self-employment to wage employment? Indeed, using the divide between 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 characteristics and very detailed social network information, together with event history data, in particular the individuals' employment records.[2] Second, we characterise the various dimensions of family networks. Lastly, we address the problem of the simultaneity bias which may affect the measure of the effect of networks on labour market outcomes by using a survival analysis that makes use of proportional hazard models for discrete-time data, and by relying mostly on the characteristics of siblings to define family networks.

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 family networks on professional transitions and Section 5 concludes.

2. Surveys, data, and definitions

2.1. 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 researchers from the French Institute of Research for Development (IRD), including the authors of this paper, under the supervision of Daniel Delaunay and Florence Boyer (Boyer and Delaunay, 2009). This survey provides data on the socio-demographic characteristics of the households and their members and also on individual events such as work experience and migration history. In addition, the survey includes very detailed information on social networks which we will describe below. An area sampling methodology guarantees the representativeness of the survey.[3] Event history and social network information were collected from half of the individuals aged 18 and over, chosen at random.[4] Thus, we collected the work histories of 1762 men and 1050 women, totalling 2812 individuals.[5]

In addition, following the approach advocated in Kanbur (2005), qualitative data are used in our analysis to complement quantitative results. In April 2009, 15 qualitative interviews were carried out with individuals who had responded to the full questionnaire.[6] 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 interviewees' social network formation and dynamics, on the resources they had acquired throughout their lives (social, human, and financial capital), on the help they received at different stages of their trajectories (schooling, marriage, housing, and job), and on the process of occupational insertion and transitions. The interviews lasted between 45 minutes and one hour and a half.

[1] A simultaneity bias in estimations may occur when workers build their network through various strategies in order to improve their occupational trajectories.

[2] See Nordman and Roubaud (2009) for an example of labour market analysis using event history data.

[3] In a first step, we 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 in the sub-area was chosen at random. All the individuals in the household were surveyed.

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

[5] Weights are applied in all calculations to take the sampling scheme into account.

[6] Using the sampling frame of the 'quantitative' survey of households, the sampling of respondents, whose interviews took place at the respondents' home and/or workplace, included individuals with diverse characteristics specifically regarding their occupations, and professional and migration experiences.

2.2. Defining and measuring family network characteristics

Following the 'egocentered' perspective, a social network is defined as a set of human contacts ("alters") known to an individual ("Ego"), with whom he/she expects to share material or intangible resources. In this paper, we focus on family ties. Using families as a measure of social networks is a way to tackle issues of endogeneity and timing, assuming that family size is not subject to endogenous changes throughout individuals' professional life. Indeed, it is recognized in the literature in economics that family 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 family ties are crucial for professional activity in the Sub-Saharan African context: when starting a business, but also when facing a professional shock (Berrou and Combarnous, 2012; Pasquier-Doumer, 2013; Fafchamps, 2002; Lourenço-Lindell, 2002). In our survey, family ties represent 60% of all the support received to find a job or to improve one's current professional activity (Pasquier-Doumer, 2010). Family, in particular siblings, may then be a good proxy for social networks as far as transitions on the labour market are concerned.

The size of networks is considered in this paper together with their tie content and resource dimension. Most of these networks were measured with a name-generating methodology in the 'quantitative' survey (McCallister and Fischer, 1978). More precisely, the respondents were asked to name all their siblings from the same mother and father who were currently alive.[7] Further questions included in a name interpreter provided information about the characteristics of the person mentioned. From this information, we were able to reconstruct the strength of ties as well as the resources embedded in the family network, captured by the socioeconomic statuses of those mentioned. These name generators allowed us to collect information on 11,017 siblings.

Three types of social network variables are computed to characterize the network in its three main dimensions, i.e. structure, resources, and strength of ties: (1) the number of siblings which aims at characterizing one dimension of the structure, Ego's network size, also called the degree of a node (Jackson, 2008); (2) the siblings' average years of schooling and dummies taking the value one if one of the siblings has a job in the public sector, which aims at capturing the resources embedded in one's family network; and (3) three 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 siblings' geographical remoteness from 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 more difficult and costly to keep in touch with family and kin (an 'out of sight, out of mind' effect), hence that the intensity of ties declines with distance (Gubert and Fafchamps, 2007; Whitehouse, 2011); and a dummy taking the value one if the individual visited a family member at least once over the past week,[10] which aims at reflecting the reciprocal dimension of ties. However, the exogenous status of the latter variable may be questionable. The variable related to visits to parents is potentially endogenous to changes in employment status if these visits aimed at showing gratitude to parents 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 long (12 years on average), which makes us believe that this variable is not endogenous to previous labour market choices, assuming that visits to show gratitude decrease with time. Indeed, many other events may shape the strength of ties. We then consider the visit dummy as a structural measure of the strength of family ties.

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 individuals' relationships with their family networks – one could object that it may not affect transitions if such transitions occurred precisely before the workers arrived in Ouagadougou, so prior to their migration. We checked this possibility and found that employment transitions taking place outside Ouagadougou concerned only 5% of workers who experienced a transition, so that this argument does not invalidate the use of such a 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.[11] In this case, distance may be correlated with unobserved worker characteristics and might just pick up the effect of abilities in the regressions. We limit this possibility by relying on 'frailty' models which consist in modelling the unobserved heterogeneity component thanks to the structure of the event history data (see Section 3).

2.3. Measuring labour market transitions

Labour market transitions are measured using work histories. In their 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 what months the events occurred. Spells are then converted into durations which are computed in years. Each spell of activity is then characterized by the activity status (employed versus unemployed), the type of employment (self-employment, wage employment, other), the sector of activity, and the type of enterprise (public versus private).

[7] We decided to limit ourselves to siblings and not to use extended family, such as cousins, uncles and aunts, as a measure of the social network. This is because we cannot capture the respondents' actual blood ties with other relatives quite perfectly. This problem is worsened by the fact that many communities of migrants in West Africa refer to each other as 'cousins' (for example the large Ivorian diaspora in Burkina Faso). As a result, not being able to take true blood ties into account may worsen the potential endogeneity of the link between social networks and labour market outcomes. Yet, an issue with the number of siblings is the possible existence of differential mortality, i.e. diverging life expectancy for different age cohorts: older cohorts of workers may have lost more brothers and sisters than younger generations of workers at the same age. Differential mortality may affect other characteristics of siblings such as their average education level, occupational status, or geographical fragmentation. To check for this possible phenomenon in the characteristics of siblings, we account for age and use crossed age-sibling effects in the regressions to determine to what extent this may affect our estimates.

[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 as the respondent, 2 if the siblings live in Ouagadougou and less than half live in the same sector of the city as 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 Faso, and 6 if less than half of the siblings live in Burkina Faso.

[9] For this variable, instead of relying on geographical distance per se calculated in kilometres (which can be computed from Ouagadougou to the village or commune of origin using geographical maps), we collected information directly from the main bus stations in Ouagadougou regarding the time and cost to reach the closest main city in the corresponding province of Burkina Faso. This ensures that we are effectively approaching a (time or monetary) cost to keep in touch with remote family, in a context where the condition of roads may vary significantly.

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

[11] The following argument mitigates the potential bias, however. We consider non-migrants and migrants who only decided to migrate to the economic capital of Burkina Faso. One may then assume that this decision to migrate is often made whatever the distance to the capital. In other words, migrants do not so much choose between places of varying distances to their home, but rather whether they will migrate to one of the secondary cities or to the economic capital. Hence, one may argue that all those who migrated and opted for the economic capital share similar unobservable characteristics implying a relatively small potential bias associated with our distance measure for them.

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' calculations.

Three different labour market transitions, called 'failures' hereafter (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 these different employment changes are defined.

For some individuals, there has been some time out of employment or of the labour market. Should this be included 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 a change of occupation for women is often a secondary outcome of a different decision, in particular 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 for this by excluding employment interruptions (Parrado, Caner and Wolff, 2007), which may distort their results. In this paper, we chose to exclude women from the analysis.[12] The main reason for this is that the number of women who have experienced 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[13] (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, it is particularly for the distinction between unemployment and inactivity periods, for instance, 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 family 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 preceded by short withdrawals from activity, i.e. those transitions which were unavoidably broken up by frictional unemployment, that is, by the time to get information about new jobs and to mobilize one's social network. In order to keep such transitions in the sample, we still consider as 'consecutive' transitions between two jobs those 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 the unemployment of discouraged workers).[14]

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 2 provides descriptive statistics of workers having experienced the three types of transitions. Looking at the first transition from unemployment to employment, two social network features diverge significantly among workers who experienced such a transition and those who had not experienced 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 experience a transition to employment have a larger family network: they declare having on average 4 siblings, while unemployed workers who did not experience such a transition declare 2.9 siblings. However, it is premature to conclude at this stage that family network capital fosters job access in the labour market.

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

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

To conclude, we attempted to hierarchize employment transitions. Due to data limitations, we cannot clearly infer a welfare gain for each transition, except for the transition of unemployment to employment. However, using Ego's average levels of education and wealth, we can highlight general trends. Workers in wage employment are at the top of the socio-economic ladder and benefit from large social networks 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 narrower social networks which are less endowed

[12] 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 was sufficiently large for women. For employment change regressions, we preferred using interaction terms with the sex dummy variable because the occurrence of job changes was very low for women, and so segmenting the global sample by sex would have consisted in 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.

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

[14] Modelling unemployment duration jointly with the specific state exited into rather than duration alone would be an interesting path of research (Lancaster, 1990; Carrasco, 1999). Considering these competing risk models implies not excluding non-consecutive changes in employment status from the sample. However, we chose not to follow this path of research, as we were constrained by low numbers of specific transitions (self-employment or wage employment) to and from unemployment.

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 Ouagadougou	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's 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	
Family network characteristics									
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	**
Dummy for siblings in public sector	0.10	0.20		0.23	0.06	**	0.06	0.04	
Strength of ties									
Distance from the birthplace to Ouaga (h)	2.65	3.35		3.58	2.36	**	2.71	2.45	
Dummy for all siblings in Ouaga	0.20	0.17		0.21	0.30		0.26	0.22	
Dummy for all siblings 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	
Dummy for visit to parents	0.41	0.29		0.35	0.41		0.30	0.37	
Number of individuals	*105*	*112*		*702*	*162*		*738*	*113*	

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

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

2.4. 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 population considered. 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 Phase 1 of the *123 Survey* (Phase 1 is a Labour Force Survey) in Ouagadougou in 2002, one can show that less than 9% of employed individuals declared a second activity (Bocquier, Nordman and Vescovo, 2010). As a result, we believe that this problem is not too severe. Moreover, using the worker's main activity is easier to understand and, from 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, either at the firm or at the worker level. 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, Nordman and Vescovo, 2010).

A potential issue with survival analysis which is often mentioned is respondents' memory problem. It relates to whether memory and recall bias for 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 for 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 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 it should minimize them 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, Riandey and Firdion (1992) in their paper matching biographical survey data and administrative registers at the individual level in Belgium.

3. Estimation strategy

3.1. Hazard models

To estimate labour market transitions and changes in employment status, we rely on a survival analysis which uses proportional hazard 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 yearly events for each individual since birth, we do not know the exact time of failure in months, but just a year interval in which the failure occurred. Hence, our survival times are interval censored rather than intrinsically discrete. For this reason, we prefer the complementary log–log model, also called the *cloglog* (see Jenkins, 2005 for further details).

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 to *cloglog* models could be logistic models. The advantage of *cloglog* models is that they are discrete-time equivalents of the widely-used Cox proportional hazard model. In practice, *cloglog* and logistic hazard models which 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).[15] 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 individuals' situation at the date of the survey. X_1 includes Ego's age in years in 2009 which allows us to control for the cohort effect, 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 background 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 analyses on the basis of information on the ownership of durable goods, housing conditions, and access to utilities.[16] An additional control is introduced for the transition from self-employment to wage employment: a dummy indicating whether the worker was employed in the agricultural sector.

We also use time-varying covariates (X_{2j}) which comprise the individual's potential experience in the labour market,[17] the time elapsed since the individual arrived in Ouagadougou at the transition time (which is equal to the survival age for non-migrants), the time elapsed since the first child's birth at the transition time (equal to zero for individuals with no children), and a period dummy taking the value one if the transition failure occurred prior to the devaluation of the CFA franc in 1994. This latter variable is introduced as a control for conjuncture and policy measure effects following the Burkinabe Structural Adjustment Programme, which may have shaped labour market insertion and dynamics.

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

$$h(j, X_j) = 1 - \exp[-\exp(\beta'_1 X_1 + \beta'_2 X_{2j+} \delta' SN + \gamma_j)] \tag{1}$$

In the model considered so far, all differences between individuals are 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 models may overestimate the degree of negative duration dependence in the true baseline hazard, and underestimate 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 unemployment or obtain better jobs faster). In this case, survivors at any given survival time are increasingly composed of observations with relatively low values of unobserved heterogeneity (discouraged or unmotivated workers) and thus 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:

$$h(j, X_j) = 1 - \exp[-\exp(\beta'_1 X_1 + \beta'_2 X_{2j+} \delta' SN + \gamma_j + u)] \tag{2}$$

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 which 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 summarise unobserved individual heterogeneity.

3.2. Analysis of family networks using principal component analysis

Following Dickerson and Green (2004), Jellal, Nordman and Wolff (2008), or Fernandez and Nordman (2009) in other contexts, we use principal component analysis (PCA) to summarise the observed information about the individual's family network in order to circumvent the potential multicollinearity of family network variables. In

[15] 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 of a model with the log of the hazard rate as the dependent variable. We also do not rely on the Andersen–Gill model (Andersen et al., 1993) because its main drawback is that it assumes no inter-individual variations of the probability of failure, and also no dependence over time (through its non-homogenous Poisson process). We believe these assumptions are too strong regarding the risk of transitions which necessarily implies some degree of inter-worker variations and time dependence.

[16] The set of variables is the ownership of a TV, radio, refrigerator, fan, bicycle, motorbike, car, computer, the ownership of housing, a WC, private kitchen, in-house running water facility, electricity, the composition of walls, a housekeeper, the 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.

[17] This experience variable is not computed from the respondent's age, years of schooling, and age at school entry (as it is usually done), but uses one property of the event history data (Nordman and Roubaud, 2009): we observe the actual age at 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.

principal component analysis,[18] 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 summarise the original data. The computed factors were rotated using an oblique rotation to ease their interpretation. If a qualitative interpretation of each of the PCA axes can be provided, which is our case, the generated PCA axes can be used as substitutes for social network variables in the labour market change regressions.

Table A1 in Appendix A reports the main diagnostics of this PCA.[19] For our purpose, the first six axes are kept, as they concentrate most of the total variance of the original variables (93%) and reflect, therefore, a fair amount of the relevant information about the individual's family network characteristics. The pairwise correlation coefficients of the characteristics of the family network and of the individual with the first six factors are then used for the interpretation of the computed factors (Table A2 in Appendix A).

The six factors are closely associated with the following characteristics: *Factor 1* corresponds to the resources related to the social capital embedded in the networks, combining education and, to a lesser extent, the activity portfolio of the network (whether its members have jobs in the public sector). *Factor 2* is mainly summarised by the distance to the region or village of origin, as it is highly correlated with the two variables describing the cost (in CFA francs) and time (in hours) 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* is highly correlated with information summarising the fragmentation of the siblings, i.e. whether they live in Ouagadougou or elsewhere. Its interpretation is very close to that of *Factor 2*, but with a restricted definition of kinship, i.e. the weakness of ties with one's biological family. *Factor 4* reflects the sibling network size. *Factor 5*, like *Factor 1*, reflects the resources embedded in the family network but gives a higher weight to resources related to labour market outcomes. Finally, *Factor 6* stresses strong ties with the extended family, as it is positively correlated with the number of visits to one's parents. More precisely, it reflects the reciprocity dimension of strong ties, as paying a visit may measure the effort provided to foster family links.

These six factors therefore reflect a wide range of social network characteristics. More importantly, we find that the factors are rather clearly defined and all have a relevant interpretation according to the literature. These network characteristics can mainly be described by the size/structure of the network, its resources (education and professional activity of its members), and the strength of its ties (geographical remoteness, fragmentation, and reciprocity).[20]

4. Results

Table 3 reports the results of the hazard model estimations for family network variables (full results are presented in Table A3 in Appendix A). 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. Family networks are approximated by the most influential family network variables in Models 1 and 3, and by the computed factors resulting from the PCA in Models 2 and 4 (see previous section).

4.1. Transition from unemployment to employment

Looking at the non-frailty Model 1, three characteristics of the network seem to influence (at the 10% level) the propensity to find a job when individuals are unemployed: the siblings' average education, with a negative effect; the distance to the area of origin, with a positive sign; and the siblings' remoteness from Ouagadougou, again with a positive sign. By taking individuals' unobserved heterogeneity into account in Model 3, we refine these estimates, and the effect of the siblings' education vanishes, while the other two significant effects are reinforced (at the 5% level).

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 greater distance between the unemployed and his/her kin in the village of origin leads to quicker access to employment. This may happen for at least two reasons. First, the greater the distance to one's family 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 45-year-old tailor, migrated to Ouagadougou, he was 14 years old and did not know anybody in Ouagadougou except for a distant friend of his father's, with whom his father engaged in the trade of kola nuts. His parents sent him to Ouagadougou with the hope that he would learn a trade. Unlike the children of his father's friend, he was undernourished and had to work hard to contribute to the expenses of the household. This led 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-year-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 suburban district. The head of her family, her father's brother, gave her some help, but only when she visited him. Because she was poor, it was very difficult for her to go across the city to visit him.

A second interpretation calls for the possible disincentive effect exerted by family networks in terms of 'earnings predation'. Such adverse incentive effects could arise if migrants feel that everything they earn needs to be shared with their close and extended family, or that labour incomes may even attract family members with whom these earnings have to be shared.[21] Demands from their kin or, more broadly, from people in the village of origin may then have a disincentive effect on their job search, and this effect gets diluted with geographical distance. Indeed, the greater the distance to the kinship network, the higher the cost for kin to observe workers' labour earnings. 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 who live in a village 15 km from Ouagadougou. They both pay regular visits to *François*'s

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

[19] Further details on this PCA can be obtained from the authors upon request.

[20] As a robustness check, we split the sample randomly into two halves and performed the PCA on each half. The results remain unchanged.

[21] The idea that family and kinship ties may imply adverse incentive effects is relatively old. It is quite often mentioned in the anthropological literature, it 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; Grimm et al., 2013).

Table 3
Hazard regression results.

Family network variables	Unemployment to employment				Wage employment to self−employment				Self-employment to wage employment			
	(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
Number of siblings	−0.0471		−0.0244		−0.00574		−0.0514		−0.00213		0.0102	
	(0.0623)		(0.0646)		(0.0559)		(0.0566)		(0.0656)		(0.0688)	
Siblings' average years of schooling	−0.0498*		−0.0397		0.00101		0.00566		−0.0694*		−0.113**	
	(0.0313)		(0.0332)		(0.0289)		(0.0299)		(0.0419)		(0.0488)	
Siblings in public sector	0.279		0.399		−0.216		−0.476		0.459		0.664	
	(0.337)		(0.342)		(0.331)		(0.374)		(0.431)		(0.465)	
Distance from the birth place to Ouaga (h)	0.0951*		0.0901**		0.0239		0.0230		0.0297		−0.0181	
	(0.0550)		(0.0422)		(0.0514)		(0.0496)		(0.0579)		(0.0601)	
Siblings' remoteness from Ouaga	0.137*		0.117**		−0.0600		−0.0655		0.0944		0.131*	
	(0.0743)		(0.0571)		(0.0759)		(0.0674)		(0.0791)		(0.0813)	
Visit to parents	−0.112		−0.0918		0.106		0.226		−0.0429		−0.218	
	(0.229)		(0.222)		(0.189)		(0.201)		(0.234)		(0.263)	
Factor 1 (Resources in human capital embedded in the network)		−0.246*		−0.192		0.0391		0.0159		−0.281*		−0.447***
		(0.146)		(0.148)		(0.132)		(0.138)		(0.185)		(0.200)
Factor 2 (Distance to the origin locality/weak ties with kinship)		0.233*		0.216*		0.0435		0.0573		0.0528		−0.0433
		(0.137)		(0.131)		(0.126)		(0.174)		(0.143)		(0.157)
Factor 3 (Fragmentation of the siblings/weak ties with siblings)		0.195*		0.172*		−0.0855		−0.189		0.186*		0.255*
		(0.107)		(0.105)		(0.124)		(0.141)		(0.126)		(0.132)
Factor 4 (Size of the sibling network)		−0.156		−0.104		0.0254		−0.0739		0.0946		0.140
		(0.131)		(0.127)		(0.114)		(0.127)		(0.141)		(0.145)
Factor 5 (Occupational resources embedded in the network)		0.134		0.172*		−0.105		−0.161		0.0882		0.135
		(0.108)		(0.105)		(0.111)		(0.121)		(0.146)		(0.155)
Factor 6 (Reciprocity/strong ties with kinship)		−0.0258		−0.0226		0.0480		0.106		−0.0246		−0.107
		(0.107)		(0.108)		(0.0879)		(0.0933)		(0.109)		(0.124)
Other controls (see Appendix A, Table A3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−4.043***	−3.737***	−4.025***	−3.662***	−4.729***	−4.868***	−4.749***	−5.061***	−5.513***	−5.353***	−5.245***	−5.311***
	(0.781)	(0.703)	(0.329)	(0.356)	(0.753)	(0.637)	(0.518)	(0.312)	(0.910)	(0.758)	(0.492)	(0.518)
Observations	1324	1324	1324	1324	10544	10544	10544	10544	10726	10726	10726	10726

Source: Ouaga2009 survey, authors' calculations.
Note: Standard errors in parentheses, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.
Heteroscedasticity is corrected with White's method in the non-frailty models.

parents, and they also receive regular visits from sisters and brothers on various occasions. 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 *François*'s family are worse off than they are. In the same vein, *Inoussa* (Interview 13), 29 years old, an apprentice at a furniture store, migrated to Ouagadougou when he was 18, from a village 18 km away, where his family still reside. He explains that he has many friends from the village who 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 family network characteristics introduced in levels with 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 the combined dimensions of the individual's family, 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 *Factor 2* and *Factor 3* exert a positive and significant effect on the probability of escaping unemployment. We thus confirm the previous positive effect of the fragmentation of siblings (*Factor 3*) and of the distance to the origin locality (*Factor 2*). The novelty here comes from the effect of *Factor 5*, which reflects the siblings' resources in terms of activity portfolio (having siblings in the public sector). Workers with such resources obtain a job faster. This may illustrate cases where unemployment is a waiting room for jobs in the public sector, a situation where having a family member in this sector helps get access to this labour market segment.

Thus, on the one hand, we find that the proximity with kinship networks 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, which leads the unemployed to limit their job search efforts. This result is very different from what is generally observed in developed countries (Bentolila, Michelacci and Suarez, 2010). This may be due to different meanings of being unemployed in the African context, where underemployment more accurately summarises different forms of distortion on the labour market and where there is no unemployment insurance. On the other hand, the presence of a relatively highly rewarding public sector compared to other labour market segments (Kuépié, Nordman and Roubaud, 2009) still seems to favour a situation where unemployed workers have incentives to queue for jobs in this sector, especially when the resource is embedded in their family network (i.e. public sector siblings).

4.2. Transition from wage employment to self-employment

As shown in Table 3, family network variables have no clear and significant effects on the propensity to experience a transition from wage employment to self-employment. This is especially true when non-frailty models are considered (Models 1 and 2). This diagnosis changes slightly if we control for unobserved individual effects (Models 3 and 4), but the overall significance of the coefficients remains poor and beyond the reach of the 10% level threshold.

These regressions still elicit the hazardous and precarious nature of self-employment, as having children[22] or having a high education level convey negative and significant effects on the transition to self-employment (see Table A3 in Appendix A).

Thus, family networks do not play a significant role in experiencing transitions from wage employment to self-employment. One of the reasons might be the low initial investment required to become self-employed in West African labour markets, as shown in Grimm, Krüger and Lay (2011) for informal activities.

4.3. Transition from self-employment to wage employment

We note two robust effects of family networks on the propensity to experience a transition from self-employment to wage employment (Table 3): the weakness of sibling ties (*Factor 3* in Model 4, or siblings' remoteness from Ouagadougou in Model 3) has a positive effect; on the contrary, the resources in human capital of this network (*Factor 1* in Model 4, or siblings' average education level in Model 3) have a negative and significant effect on this propensity (at the 5% level in the frailty specification). Consequently, a high level of resources in human capital embedded in the network is associated with a longer duration in self-employment. This may mean that individuals with a high level of human capital resources have a higher opportunity cost to transition from self-employment to wage employment compared with workers who have a lower level of these resources. Indeed, having siblings with a higher education level may help access credits and/or information about market opportunities.

Looking at the coefficients on other individual characteristics in Table A3 in Appendix A, it appears that recent migrants, in particular those who used to be farmers, are more concerned with this transition, since self-employment in the agricultural sector and the time elapsed since the individual arrived in Ouagadougou both have a significant effect, in particular in the frailty specification (3), positive in the first case, negative in the second. More educated workers have a higher propensity to transition from self-employment to wage employment, probably because of selection into migration, as illustrated by *Boukaré*'s work history (Interview 9), a 34-year-old building custodian, who was a self-employed farmer and was selected by his family to migrate to Ouagadougou because he was the most educated in his family.

This result suggests that workers without strong sibling ties are encouraged to make more efforts to socialise as they may not find continuous support from their siblings. For instance, *Frederick* (Interview 5), a 29-year-old man resuming his studies at the time of the survey, whose older brother lives in another city (Koudougou), spends a lot of time at his 'grin', an informal organisation of individuals of the same generation, living generally in the same neighbourhood, and who meet up in the street to drink tea, chat, and play cards. Kieffer (2006) defines a 'grin' in Ouagadougou as a place where individuals are engaged in reciprocal relationships, especially with "*big brothers*" who play a protective role, are solicited for occupational projects, offer job opportunities, and receive services in exchange. For Frederick, this 'grin' is an essential source of information, which allows him to obtain various professional contacts and job opportunities. Through his 'grin', he found wage employment as an enumerator for an international NGO. He also developed a network of truck rental companies and he met a logistician to discuss this career path that he aims for.

These results seem to confirm Granovetter's predictions on the strength of weak ties: weak ties allow self-employed workers to get

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

better access to information on wage employment opportunities. Introducing the resource dimension, however, changes the perception of the role of family networks in the transition from self-employment to wage employment. Indeed, kinship networks endowed with high educational resources seem to discourage self-employed workers from becoming wage workers. Knowing that the wage jobs obtained through one's family network after a self-employed job may be of poor quality, as discussed by the descriptive analysis (Table 2) and confirmed by our qualitative interviews, we may conclude that weak ties increase access to information on jobs, but that this information is of little value.

By contrast, having a good quality network may encourage workers to be self-employed. Indeed, in some cities and activities of West Africa, it is not uncommon to find unregistered self-employed workers, therefore belonging to the informal sector, following some of the management rules of modern businesses. A few authors have thus identified an 'upper segment' of the informal sector, which may be less vulnerable in terms of earnings than the bulk of wage employment situations (see Fields, 2004; Bocquier, Nordman and Vescovo, 2010). Analysing the qualitative interviews also illustrates the role of family network resources and the strength of non-kinship ties to experience upward mobility within the self-employment status. *Awa* (Interview 10), a highly educated 37-year-old woman born in Bamako (Mali), who migrated following her husband, explains the success of her textile trade by the help of her friends and her husband's friends to create a clientele, but also to invest in her activity. According to her, "*friends are more able to understand money issues*", implying more than one's family.

The crossed effects of the family variables with age complement and somehow confirm these findings: strong ties with the extended family measured by the number of visits paid to parents (*Factor 6*) exert a negative and significant effect (at the 10% level) on transition from self- to wage employment, but this negative effect diminishes slightly with workers' age. This refinement reinforces the finding that strong family ties play a stabilising role in labour market dynamics: having frequent interactions with one's family increases the probability of remaining in the same activity status for self-employed workers.

5. Conclusion

The aim of this paper is to shed light on the role of family 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 family network has the strongest effect on these transitions, by distinguishing the resources embedded in the network from the structure of the network and the strength of its 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 questionnaire. 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 family networks have a significant effect on the transitions of individuals on the labour market, except for the transition from wage to self-employment. In addition, the results differ depending on the type of transition and on the dimension of the family network considered, i.e. the sibling network size, the resources available in the network, and the strength of ties.

The family network size, approached by the number of siblings, appears not to matter much in labour market dynamics. Size is far from being the most important dimension of family 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 family network may dominate its informative function in a context where there is no formal safety net scheme for unemployed workers.

Regarding the strength of ties, strong ties seem to play a stabilising role in labour market dynamics. Indeed, having a network endowed with strong ties, in particular strong family ties, increases the probability of remaining in the same activity status for self-employed and unemployed workers. Strong ties seem to be of little use for access to wage employment, except for access to the public sector. During their job search, unemployed workers who have strong ties in their family networks may tend to limit their efforts to find a job. These results reinforce the idea that the safety net function of strong ties dominates their informative function. 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 greater the network resources, the weaker the incentive to find a job, and the more profitable it is to evolve within the self-employment status.

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

Appendix A

Table A1
Principal component analysis (PCA) of social network characteristics.

Factors	Eigenvalues	Difference	Proportion	Cumulative
Factor 1	2.86287	0.33255	0.2863	0.2863
Factor 2	2.53032	1.33877	0.2530	0.5393
Factor 3	1.19155	0.14585	0.1192	0.6585
Factor 4	1.04571	0.09374	0.1046	0.7630
Factor 5	0.95197	0.27014	0.0952	0.8582
Factor 6	0.68183	0.26611	0.0682	0.9264
Factor 7	0.41572	0.21282	0.0416	0.9680
Factor 8	0.20290	0.12171	0.0203	0.9883
Factor 9	0.08120	0.04527	0.0081	0.9964
Factor 10	0.03592	.	0.0036	1.0000

Source: Ouaga2009 survey, authors' calculation.

Table A2
Pairwise correlation coefficients between PCA factors, kinship network and individual characteristics.

	Factor 1 Resources in human capital embedded in the network	Factor 2 Distance to the origin locality/weak ties with kinship	Factor 3 Fragmentation of the siblings/weak ties with siblings	Factor 4 Size of the sibling network	Factor 5 Occupational resources embedded in the network	Factor 6 Reciprocity/ strong ties with kinship
Social network characteristics						
N siblings	0.2806*	0.0780*	0.1987*	**0.9077***	0.1662*	0.0339
Siblings' average years of schooling	**0.9723***	0.1621*	−0.0371	0.2551*	0.3448*	0.0220
Siblings' max years of schooling	**0.9627***	0.1788*	0.0195	0.3886*	0.3749*	0.0434
Siblings in public sector	**0.4628***	0.1295*	0.0364	0.2092*	**0.9546***	0.0282
Distance from the birth place to Ouaga (h)	0.1406*	**0.9902***	0.4153*	−0.0556	0.1248*	0.0606
Distance from the birth place to Ouaga (CFA)	0.1848*	**0.9905***	0.3963*	−0.0123	0.1168*	0.0613
Siblings' remoteness from Ouaga	−0.1393*	0.3446*	**0.8959***	−0.1847*	0.1768*	0.0164
N siblings in Ouaga	0.3250*	−0.2436*	**−0.5211***	**0.8136***	−0.0053	0.0039
N siblings abroad	0.1726*	0.3709*	**0.8228***	0.2087*	−0.1187*	−0.0256
Visit to parents	0.0356	0.0600	−0.0049	0.0305	0.0300	**0.9995**
Individual characteristics						
Aged 26–35 years	0.1286*	0.0125	0.0203	0.1455*	0.0045	−0.0133
Aged 45 years and more	−0.2364*	−0.0087	−0.0015	−0.2959*	0.0262	0.0458
Islam	−0.2136*	0.0478	−0.0142	−0.0497	−0.1276*	−0.0267
Moore	−0.2144*	−0.3654*	−0.2224*	0.0179	−0.1409*	−0.0570
Born in Ouaga	0.2107*	**−0.5455***	−0.3746*	0.2533*	−0.1166*	−0.0593
Primary school	0.0377	−0.0488	−0.1178*	0.1123*	−0.0712*	0.0174
Lower secondary school	0.2069*	0.0103	−0.0354	0.0731*	0.0239	−0.0346
Higher secondary school and above	**0.4737***	0.2275*	0.1273*	0.1467*	0.2965*	0.0681

Source: Ouaga2009 survey, authors' calculation.
Note: *Means significant at the 1% level.
In bold: coefficients with absolute value higher than 0.45.

Table A3
Hazard regressions results (full table).

Variables	Unemployment to employment				Wage employment to self-employment				Self-employment to wage employment			
	(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	0.190	0.203	0.271	0.284	0.131	0.141	0.0967	0.0959	−0.351	−0.351	−0.360	−0.367
	(0.230)	(0.230)	(0.249)	(0.233)	(0.195)	(0.195)	(0.207)	(0.235)	(0.218)	(0.218)	(0.237)	(0.225)
Moore	0.169	0.211	0.176	0.214	0.252	0.233	0.260	0.231	0.189	0.198	0.0786	0.102
	(0.268)	(0.274)	(0.278)	(0.268)	(0.294)	(0.297)	(0.264)	(0.297)	(0.359)	(0.362)	(0.343)	(0.368)
Primary school	0.731**	0.711**	0.445	0.436	−0.0574	−0.0813	−0.0802	−0.103	0.559**	0.553**	0.530*	0.521*
	(0.333)	(0.329)	(0.345)	(0.342)	(0.246)	(0.247)	(0.265)	(0.278)	(0.274)	(0.275)	(0.313)	(0.307)
Lower secondary school	0.0967	0.0521	−0.0421	−0.0767	−0.586	−0.599	−0.418	−0.419	0.758	0.720	1.124**	1.067**
	(0.419)	(0.419)	(0.438)	(0.429)	(0.393)	(0.393)	(0.388)	(0.386)	(0.461)	(0.468)	(0.473)	(0.486)
Higher secondary school and above	0.847**	0.796*	0.649	0.620	−1.027**	−1.054***	−0.913**	−0.911**	0.967	0.926	1.531**	1.445**
	(0.417)	(0.416)	(0.469)	(0.450)	(0.401)	(0.399)	(0.403)	(0.449)	(0.613)	(0.616)	(0.623)	(0.656)
Potential experience (years)	0.0659**	0.0618**	0.0487**	0.0452***	0.0253	0.0263	0.0409***	0.0428**	0.0637**	0.0649**	0.0969***	0.0984***
	(0.0314)	(0.0313)	(0.0213)	(0.0150)	(0.0254)	(0.0254)	(0.0158)	(0.0185)	(0.0323)	(0.0323)	(0.0305)	(0.0213)
Potential experience squared	−0.00278***	−0.00273***	−0.00217***	−0.00213***	−0.000788	−0.000799	−0.000942**	−0.000964**	−0.00114	−0.00113	−0.00162**	−0.00160***
	(0.000952)	(0.000944)	(0.000525)	(0.000524)	(0.000586)	(0.000587)	(0.000387)	(0.000390)	(0.000708)	(0.000709)	(0.000690)	(0.000503)
Time since arrival in Ouaga	0.0166	0.0194	0.0182*	0.0198	0.0109	0.00976	0.0137	0.0120	−0.0150	−0.0149	−0.0173*	−0.0164*
	(0.0143)	(0.0145)	(0.0100)	(0.0131)	(0.00874)	(0.00867)	(0.00878)	(0.00937)	(0.00942)	(0.00937)	(0.0100)	(0.00964)
Time since first child's birth	−0.0405*	−0.0424*	−0.0522***	−0.0541**	−0.0599***	−0.0591***	−0.0621***	−0.0619***	−0.0150	−0.0158	−0.00478	−0.00601
	(0.0243)	(0.0244)	(0.0199)	(0.0239)	(0.0174)	(0.0174)	(0.0172)	(0.0163)	(0.0187)	(0.0188)	(0.0196)	(0.0192)
Agricultural sector									1.175***	1.181***	1.244***	1.268***
									(0.242)	(0.241)	(0.260)	(0.259)
Standard of living index	0.163	0.143	0.0849	0.0704	−0.183	−0.182	−0.130	−0.132	−0.0711	−0.0783	−0.0974	−0.106
	(0.157)	(0.155)	(0.156)	(0.154)	(0.126)	(0.127)	(0.130)	(0.170)	(0.163)	(0.162)	(0.181)	(0.179)
Birth order	0.0342	0.0495	0.00762	0.0235	0.0525	0.0480	0.0841	0.0798	−0.0179	−0.0348	−0.0699	−0.0829
	(0.103)	(0.102)	(0.0905)	(0.0892)	(0.0820)	(0.0818)	(0.0809)	(0.0790)	(0.0940)	(0.0928)	(0.0937)	(0.0907)
Age	0.0103	0.0127	0.0128	0.0157	0.0102	0.0112	0.00573	0.00687	−0.00998	−0.00871	−0.0240**	−0.0227*
	(0.0242)	(0.0243)	(0.00835)	(0.0112)	(0.0121)	(0.0121)	(0.0113)	(0.0112)	(0.0145)	(0.0144)	(0.0112)	(0.0120)
Devaluation dummy	0.0186	0.0128	−0.0627	−0.0649	−0.171	−0.167	−0.370	−0.376	−0.0197	0.00169	−0.164	−0.126
	(0.253)	(0.256)	(0.240)	(0.242)	(0.289)	(0.289)	(0.297)	(0.327)	(0.324)	(0.323)	(0.320)	(0.315)
Family network characteristics			See Table 3				See Table 3				See Table 3	
Constant	−4.043***	−3.737***	−4.025***	−3.662***	−4.729***	−4.868***	−4.749***	−5.061***	−5.513***	−5.353***	−5.245***	−5.311***
	(0.781)	(0.703)	(0.329)	(0.356)	(0.753)	(0.637)	(0.518)	(0.312)	(0.910)	(0.758)	(0.492)	(0.518)
ln_varg			−13.83	−13.68			−13.89	−14.72			−13.67	−14.02
			(380.0)	(320.6)			(551.4)	(1,042)			(447.4)	(544.0)
Observations	1324	1324	1324	1324	10544	10544	10544	10544	10726	10726	10726	10726

Source: Ouaga2009 survey, authors' calculation.
Note: Standard errors in parentheses, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

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