African Journal of Agricultural and Resource Economics Volume 13 Number 2 pages 107-126

Labour market and intra-household dynamics in urban Tanzania

Sarah Bridges
School of Economics, Nottingham University, Nottingham, UK. E-mail: sarah.bridges@nottingham.ac.uk

Alessio Gaggero*
School of Business, Nottingham University, Nottingham, UK. E-mail: a.gaggero@nottingham.ac.uk

Trudy Owens
School of Economics, Nottingham University, Nottingham, UK. E-mail: trudy.owens@nottingham.ac.uk

* Corresponding author

Abstract

While a large body of literature documents the existence of informal arrangements to share risk across and within households, there has been little research on the various coping strategies through which risk sharing takes place, and how these strategies function. This study attempts to fill this gap in the literature and examine whether, and to what extent, individual labour-supply behaviour is one of such coping strategies used by households facing risk. Our hypothesis is that, as with a small business, individuals adjust their employment behaviour in the event that one of their household members experiences a variation in their labour supply, that is, either gains or loses a job. Using a unique dataset that collects employment histories for each family member in Tanzania, our results confirm our hypothesis and show that the labour supply of the household members is an important determinant of employment transitions, and that these effects are greater for women than for men. In the context of low-income countries, we interpret these findings as evidence that the household works as a risk-sharing institution built around women's labour supply.

Key words: intra-household risk sharing; labour supply; employment histories; hazard model

1. Introduction and motivation

Both in developed and developing countries, individuals tend to rely on their family and household members to cope with risk. This is especially true in the context of developing countries, where social safety nets are incomplete and in some cases non-existent, and shocks can be catastrophic. A large body of the literature documents the existence of informal arrangements that allow households to share risk within their villages or communities. This literature studies the ability of households to smooth their consumption over time and against income fluctuations (Deaton 1991; Mace 1991; Townsend 1994; Udry 1994). Building on this literature, Dercon and Krishnan (2000) investigate and show the existence of risk sharing between household members. There has been little research, however, on the various coping strategies through which risk sharing takes place within the household, and how these strategies function.

In this paper, we attempt to fill this gap in the literature and examine whether, and to what extent, individuals' labour-supply behaviour is one of such coping strategies used by the household in the face of risk. Indeed, in the absence of insurance networks, individuals may fall back on the only productive asset they own, namely their labour, to cope with idiosyncratic shocks. Our hypothesis is that, like in a small business, individuals adjust their employment behaviour in the event that one of their household members experiences a variation in the labour supply, that is, either gains or loses a

job. In order to test this hypothesis, we use a dataset of urban households in Tanzania. The data provides records of employment histories for each household member since they left formal schooling. This allows us to observe when an individual gains or loses a job and whether her household members adjust their labour-supply behaviour in response to these changes. Controlling for unobserved heterogeneity, we use a discrete-time mixed proportional hazard (MPH) model to estimate the effect of a change in labour supply of the household members on entries into and exits out of employment.

Overall, the results confirm our hypothesis and show that the labour supply of the household members is an important determinant of employment transitions, and that these effects are greater for women than for men. We interpret these findings as evidence that, in the context of developing-income countries, the household works as a risk-sharing institution built around women's labour supply. Motivated by anecdotal evidence collected in the field, we put forward and discuss the hypothesis that the household enterprise is at the core of risk sharing amongst household members. The key insight of our hypothesis is that, in the context of developing countries, the household enterprise works as an unemployment insurance mechanism, in that individuals who lose their jobs can offer their labour to the household enterprise, rather than being idle whilst waiting for new job offers.

Notably, our results are robust to two main checks. First, one can argue the estimated results to be driven by town-specific trends, either upturns or downturns, which might have caused both the change in labour supply experienced by the household member and the associated change in the labour supply of the individual. To address this issue, we add to the baseline model a set of variables showing the interaction between town and time dummies, and find our results to be consistent. Second, the validity of our findings depends crucially on the reliability of the recall data used for the analysis. To dispel potential concerns regarding the data, we run the estimations using the most recent 25 years of recall data and, despite the reduction in sample size, find the results to be virtually unchanged.

The remainder of the paper is organised as follows. In section 2, we present the conceptual framework and the related literature. The methodology and the econometric framework are explained in section 3. In section 4, we present the data and the descriptive analysis. Section 5 documents and discusses the econometric results, and finally section 6 concludes.

2. Literature review

This study lies between two strands of the existing literature. The first strand is concerned with the literature of risk sharing in developing countries. The basic framework of risk-sharing behaviour is given by Udry (1994), who shows that if risk is shared efficiently in a village, household consumption levels should not be affected by variations in household income, but should be a monotonic function of the average consumption level in the village. Empirical tests of this theory only find evidence of partial risk sharing across households (see, for example, Townsend (1993, 1994) for Thailand and India, Morduch (1991) for India, and Deaton (1997) for Cote d'Ivoire).[1]

Dercon and Krishnan (2000) build on the above approach and examine the existence of risk-sharing behaviour between household members. Using panel data from rural households in Ethiopia, they investigated whether individuals are able to smooth their nutritional level over time in the face of idiosyncratic health shocks. In the presence of risk sharing within the household, income is pooled and idiosyncratic health shocks are expected not to have a statistically significant effect on the individual's nutritional level. They find evidence of risk-sharing for richer households. Poorer households, instead, are found to be less successful in smoothing nutritional levels across their

[1] Rosenzweig (1988) and Fafchamps and Lund (2003) show that risk sharing across households usually occurs through the giving of gifts and informal loans.

members. In this paper, we also examine risk sharing between household members but, unlike Dercon and Krishnan (2000), we focus our investigation on one potential coping mechanism through which risk sharing occurs between household members, namely the individual's labour supply.

Further, our work relates to the study of Skoufias and Parker (2002), who use variations in unemployment rates in metropolitan areas in Mexico to estimate how labour market shocks affect the time allocation of adult members. Their findings suggest that, in areas with a positive female unemployment growth rate, men attempt to compensate for the losses of income experienced by their women by working for longer hours. Similarly, Bhalotra *et al*. (2010) investigate to what extent women's labour supply is affected by changes in country-level GDP. Their findings suggest that, in Africa, women exhibit pro-cyclical employment behaviour, namely they increase their labour supply during upturns and decrease their labour supply during downturns. In Asia and Latin America, on the other hand, women exhibit counter-cyclical employment behaviour, and the authors argue that these differences in employment behaviour may be driven by differences in the family structure.

This paper also investigates individuals' labour-supply behaviour as a coping mechanism used by the household in the face of risk, but our data of employment histories allows us to investigate household risk-sharing behaviour in greater depth. In contrast with the studies mentioned above, we are able to study changes in employment behaviour in response to specific variations in the labour supply of the household members, rather than in response to aggregate macroeconomic trends or shocks.

The second relevant strand of the literature we relate to deals with intrafamilial decisions of labour supply. Whether we consider unitary or collective models, this literature documents that the labour-supply choices of one individual are intertwined with the labour supply of his/her family members. In particular, in the presence of returns to specialisation in home production and in the labour market, this literature explains why some members are more likely to offer their services as wage earners while others tend to specialise in home production. An implication of this model is that, if the main earner (the husband) loses his position in the labour market, the second earner (the wife) will be motivated to temporarily enter the labour market to make up for the loss of income. In the literature, the temporary increase in labour supply of the wife in response to a spell of unemployment of the husband is called the added worker effect (AWE). The theoretical framework of the AWE was provided by Ashenfelter and Heckman (1974), and more recently by Attanasio *et al*. (2005). Empirically, the investigation of the AWE has proven to be challenging.

Mincer (1962), using data of the largest northern metropolitan areas in the United States, finds a strong and negative association between the proportion of women employed during the year and the number of weeks worked by the husbands. This study, however, only documents that wives' labour-force participation is higher in areas where husbands work a fewer number of weeks, but it provides little evidence on the causal relationship between the two phenomena. Heckman and Macurdy (1980) address this issue by means of individual-level panel data and find no significant evidence that the amount of hours husbands spend in unemployment has an effect on changes in wives' labour supply. Finally, our work is particularly related to Lundberg (1985), who studies the extent to which wives' transition probabilities, from and to different labour market states, are affected by the labour supply of their husbands. Using monthly employment histories of families from Seattle and Denver, her findings provide evidence of the AWE for the sample of white people, but she finds opposite results for black people. A potential limitation of this paper, however, is that modelling women's transition probabilities as a function of a static measure of husband's labour supply may suffer from an endogeneity problem if individuals mate according to preferences for labour supply behaviour. Similarly to Lundberg, we investigate whether individuals' transition probabilities are linked to the labour supply of their household members, but we develop Lundberg's specification by modelling individuals' labour-supply behaviour as a function of a dynamic (as opposed to static) measure of labour supply of the household members.

3. Methodology

In this paper, we use transition data to answer our research question. As the name suggest, these types of data record movements of individuals from one labour market state to the other, that is, from employment to unemployment, or from inactivity to employment. The most commonly used method to analyse this data is by means of survival analysis. Formally, let T be a random variable denoting the duration of a certain spell, with cumulative distribution function $F(t)$ and probability density function $f(t)$. The survivor function is defined as:

$$S(t) = 1 - F(t) = \Pr(T > t). \quad (1)$$

The sample counterpart of the survivor function is given by:

$$\widehat{S(t)} = \prod_{j|\, t_j<t}(1 - \frac{d_j}{n_j}), \quad (2)$$

where d_j represents the number of persons observed to make the transition from one labour market state to the other, at time t_j, and n_j is the number of persons who are yet to make a transition at time t_j. Equation (2) is known as the Kaplan-Meier estimate of the survivor function and gives the proportion of individuals who remain in the certain (labour market) state at each time interval.

We can now define the probability that a person who has occupied a state for a specified time *t* leaves in a short period of time after *t*, namely the hazard function. Formally, the hazard function, denoted $\mathrm{h(t)}$, is the probability of exiting a certain (labour market) state in the interval of time $[\mathrm{t}, \mathrm{t}+1)$, conditional on being in that state up to time *t*. Using the notation from above, the hazard function is defined as:

$$\mathrm{h(t)} = \Pr(t < T < t+1 \,|\, T > t). \quad (3)$$

In this study, not only are we interested in the estimation of the hazard function per se, but especially in its determinants. What causes individuals to transition from one labour market state to the other? And to what extent does the labour supply of other household members affect the hazard? To do this, we focus on two specific transitions: employment exits and entries. We study these transitions separately.[2] In is important to emphasise that each transition is associated with a different sample. For example, we estimate the probability of transitioning out of employment for the subset of individuals who are employed. Likewise, when we estimate employment entries, we only consider those individuals who are in a non-employed state. In order to carry out the analysis we use a discrete-time duration model. The choice of using these models is dictated by the format of our data. Conventional OLS or binary models, in fact, cannot handle censoring issues (see, for example, Jenkins 2005).

Drawing from Jenkins (1995), in order to estimate a discrete-time duration model we reorganise the data in a person-year identifier (as opposed to the current person-spell identifier). To do this, we use the *episode-splitting* routine, and split the spells of each individual into years. In other words, we move from a dataset in which individual *i* contributes for S_i rows (one row for each spell) to a dataset

[2] Note that, in doing this, we are implicitly pulling together in the category of non-employed both individuals who are unemployed and those who are inactive. While this may be a strong simplification, it is a necessary compromise we have to make in the analysis.

in which i contributes for T_i rows (one row for each year). Assuming that the covariates affect the hazard in a complementary log-log link (*cloglog*), the model we are going to estimate is:[3]

$$Y_{it} = \alpha + \beta G_{it-1} + \emptyset L_{it-1} + X'_{it}\gamma + \mu(t) + \varepsilon_{it}, \quad (4)$$

where $Y_{it} \equiv \log[-\log(1 - h(t, r\,\boldsymbol{X_{it}}|a_i))]$ is a (sequential) zero-one indicator that takes the value of unity when individual i transits from one labour market state to another. The term G_{it-1} is a sequential dummy variable that equals one if a household member of individual i gained a job and, similarly, L_{it-1} is a sequential dummy that equals unity in the event that a household member of i lost a job.[4] Equation (4) shows that we exploit the timing of the events in order to avoid potential simultaneity issues, as the changes in labour supply of the household members occur before transitions are observed. The terms of main interest are β and $\emptyset$, which measure the extent to which the hazard function of member i is affected by a job gain or a job loss experienced by a household member. In this case, β and $\emptyset$ have causal interpretation only under the assumption that a job gain or a job loss experienced by the household members is exogenous.[5] This may, however, be too strong an assumption. For example, it is quite likely that a job gain or a job loss occurred by a household member may, in fact, be an endogenous choice of the individual, or the household, rather than an exogenous variation in the labour supply. We address this issue by using mixed proportional-hazard (MPH) models. The main advantage of these models is that they allow the inclusion of unobserved heterogeneity, which we denote a_i, using a Gamma mixture distribution.[6]

Further, the term $\boldsymbol{X_{it}}$ is a person-specific vector of covariates, and γ is its associated vector of parameters to be estimated. The vector of covariates includes the demographic attributes of the individual, a full set of human capital variables and town dummies.[7] The term $\mu(t)$ represents the baseline hazard, which summarises the pattern of duration dependence that is common to all individuals.[8] Since the shape of the baseline hazard is not the primary interest of this study, we choose a piece-wise constant specification in which the baseline hazard is assumed to be constant within each of the intervals defined.

4. Data and descriptive analysis

This study uses three rounds (2004, 2005 and 2006) of the Tanzania Household Urban Panel Survey (THUPS). The survey was conducted by the Centre for the Study of African Economies (CSAE) at Oxford University, in collaboration with the Tanzania National Bureau of Statistics (NBS). The THUPS is a labour market survey of urban households that collects information on incomes, labour market experiences and educational attainment for labour force participants between the ages of 15 and 65. Both workers in the formal and informal sector were interviewed. The sample is based on a

[3] This functional form is chosen as it is the natural discrete-time counterpart of the underlying continuous-time proportional hazard model (Prentice & Gloeckler 1978).

[4] We acknowledge the fact that considering any labour adjustment a coping mechanism may be a strong assumption. Ideally, we would estimate the labour-supply decision of household members in response to other shocks, such as illness and death of a household member, but unfortunately our data does not allow to do this.

[5] In the literature of (dynamic) treatment effects, this assumption is referred as the *no anticipation assumption*, and it requires subjects not to change their behaviour before treatment occurs (see, for example, Abbring and Van den Berg 2003).

[6] Nicoletti and Rondinelli (2010), however, provide evidence that MPH models are robust to misspecification of the unobserved heterogeneity functional form.

[7] Attempts were made to add to the model a dummy variable taking the value of unity if, during the same spell, other household members either gained or lost a job. However, this variable was never significant in the regressions, and therefore was omitted.

[8] We also include in the matrix of regressors parents' schooling, as it may be that better educated parents are better connected in the labour market, and hence influence individuals' labour market transitions from one job to the other and from one labour market state to the other.

stratified random draw of households from the 2000 Household Budget Survey (HBS) and covers the main urban areas of Tanzania, including Arusha, Dar es Salaam, Iringa, Morogoro, Mwanza and Tanga. For the analysis, we consider all individuals who appear in the survey. This results in a sample of 1 065 individuals.

We exploit two features of the THUPS in order to carry out our investigation. Firstly, the data includes a collection of employment histories. During the first and second round of the survey, not only were individuals asked about their current occupation, but also their employment history since they left full-time school.[9] Specifically, the survey records information for each individual on each labour market state individuals experienced, the time spent in each labour market state and the dates on which transition from one state to the other took place.[10] In other words, we have spell data organised in a person-spell identifier, in which individual *i* contributes to the dataset for *i* rows, that is, one row for each spell of labour market state reported.[11] The second feature of the data we exploit in this study is that THUPS is a household survey, and therefore includes employment histories for all household members. By matching the various employment histories of each household member over time, we are able to observe when a household member experiences a change in his/her labour supply, either a job gain or a job loss, and whether, and to what extent, other household members adjust their employment behaviour in response to this change.[12]

We report the descriptive statistics of the main variables of interest in Table 1. In columns (1) and (2), we distinguish between men and women respectively, and in column (3) we report the *p*-value of a two-sided test that compares the two groups. The table shows that, on average, the men and women are approximately 39 and 36 years old respectively. Men appear to be significantly more educated than women, reporting almost an additional year of completed schooling. Moving to labour market status, Table 1 shows that 80% of individuals in the sample report to be currently employed. Men are 4% more likely than women to be employed (*p*-value = 0.052). As expected, the majority of individuals work in the household enterprise, either with or without employees. In particular, we observe that only a small proportion of individuals working in the household enterprise are entrepreneurs (e.g. have employees), at 31% and 17% for men and women respectively, and the average number of employees ranges from one to two. This confirms the nature of the household enterprise to be a small type of informal household-based activity. The table documents that men are significantly more likely than women to have a wage job. Relative to men, women are more likely to work in the household enterprise (without employees) and are more likely to be out of the labour force.

[9] Recall data in the second round was collected only for individuals who were missed during the course of the first round.
[10] As the third round of the survey does not collect recall data, we only use it to update the current occupation of the individuals. The findings are robust to the exclusion of this round from the analysis.
[11] It is important to highlight that individuals reported the employment histories of their main jobs, that is, they did not report whether they were holding other jobs simultaneously.
[12] Note that there are no unemployment benefits in Tanzania.

Table 1: Descriptive statistics

	(1) Men	(2) Women	(3) *p* -value
Characteristics			
Age	39.387 (14.563)	36.260 (12.515)	0.000
Years of schooling	7.829 (3.858)	7.191 (3.775)	0.007
Father's years of schooling	6.565 (5.137)	6.891 (5.293)	0.368
Mother's years of schooling	3.906 (4.276)	4.271 (4.438)	0.219
Years of work experience	19.866 (17.183)	13.837 (12.907)	0.000
Years of tenure	11.849 (10.648)	9.706 (9.643)	0.001
Earnings in US dollars	23.885 (38.503)	14.765 (34.039)	0.000
Household structure			
HH Head (= 1)	0.704 (0.457)	0.211 (0.408)	0.000
HH Size	2.676 (1.644)	2.693 (1.562)	0.864
Married (= 1)	0.679 (0.468)	0.599 (0.491)	0.014
Number of children	2.867 (2.830)	2.717 (2.332)	0.392
Labour market status			
Employed (= 1)	0.783 (0.317)	0.657 (0.361)	0.052
Wage employed (= 1)	0.367 (0.483)	0.240 (0.427)	0.000
Self-employed (= 1)	0.518 (0.500)	0.592 (0.492)	0.015
Entrepreneur (= 1)	0.312 (0.464)	0.177 (0.382)	0.001
Number of employees	2.027 (1.317)	1.132 (0.804)	0.001
Not in labour force (= 1)	0.136 (0.122)	0. 273 (0.248)	0.000
Unemployed job seeker (= 1)	0.080 (0. 475)	0.073 (0. 530)	0.000
Observations	531	534	1 065

Source: Tanzania Household Urban Panel Survey.

Note: The summary statistics presented above are for the sample of individuals who appear at least in one of the waves of the THUPS. For individuals who appear more than once, we consider in this table only the most recent information available. The statistics for wage employed and self-employed are for the sample of workers. The statistics of the number of employees is for the sample of entrepreneur. Standard deviations are reported in parentheses.

In Table 2, we report the proportion of labour market transitions that occurred in the sample of interest. As in Table 1, we distinguish in columns (1) and (2) between the sample of men and women, and in column (3) we report the *p*-value of a two-sided test that compares the two groups.[13] Starting from the transitions of interest – employment entries and exits – we document that only a small proportion of the sample reported to have left a job. The table reports that women are significantly more likely to exhibit this transition than men. Specifically, the percentage of people who exit employment is 5.6% and 8.9% for men and women respectively. Approximately 40% of individuals

[13] Note, in the table we also report, in square brackets, the actual number of transitions that occurred.

experienced a transition from non-employment to employment. Again, women are significantly more likely than men to experience this transition.

Table 2: Labour market transitions

	(1) Men	(2) Women	(3) *p* -value
Exit employment	0.056 (0.230) [60]	0.089 (0.284) [102]	0.003
Enter employment	0.400 (0.490) [428]	0.437 (0.496) [503]	0.080
From wage job to:			
Non-working	0.023 (0.151) [25]	0.030 (0.169) [34]	0.368
HH enterprise	0.079 (0.271) [85]	0.035 (0.183) [40]	0.000
A different wage job	0.118 (0.322) [126]	0.059 (0.236) [68]	0.000
From HH enterprise to:			
Non-working	0.014 (0.118) [15]	0.020 (0.140) [23]	0.280
Wage job	0.066 (0.249) [71]	0.024 (0.154) [28]	0.000
A different business	0.036 (0.187) [39]	0.029 (0.167) [33]	0.299
From non-working to:			
HH enterprise	0.099 (0.299) [106]	0.182 (0.386) [210]	0.000
Wage job	0.125 (0.331) [134]	0.095 (0.293) [109]	0.021

Source: Tanzania Household Urban Panel Survey.
Note: The summary statistics presented above show the proportion of individuals who experienced a certain labour market transition over his/her recall data. Standard deviations are reported in parenthesis. The actual number of observations are reported in squared brackets.

Table 2 shows that men are significantly more likely than women to move from a wage job to work in the household enterprise. Specifically, the table reports that 8% of men transit from a wage job to the household enterprise, while the same value for the sample of women is 3.5%. Similarly, men are more likely to exhibit the opposite transition, namely from the household enterprise to a wage job. The percentage of individuals who shift from the household enterprise to a wage job is 6.6% and 2.4% for the sample of men and women respectively. Moreover, men are more likely to switch between different wage jobs; this transition occurred to 12% of the sample of men against 6% of the sample of women. Finally, the table reports that almost 20% of the sample of women transit from a non-working state to working in the household enterprise. Overall, the presented statistics suggest that the women in the sample are more likely than men to move in and out of employment; men, on the other hand, appear to be significantly more likely than women to switch between jobs and job types.

By means of the survival function, we begin to show some graphical evidence of whether individuals adjust their employment behaviour in response to changes in the labour supply of their household members. In Figure 1 we draw Kaplan-Meier estimates of the survivor function comparing individuals whose household member experienced a job gain (graph on left) and a job loss (graph on right) respectively. While it appears from the graph on the left in Figure 1 that the labour supply of the individual is not affected by job gains of other household members, the graph on the right shows clearly that individuals whose household members experience a job loss are more likely to transition to another labour market state. Similarly, in Figure 2, we compare Kaplan-Meier estimates of the survivor function between men and women. In particular, the graph on the left shows that, in the event a household member experienced a job gain, women are more likely to change their employment behaviour relative to men. We report the same exercise in the graph on the right in Figure 2, but comparing men's and women's labour behaviour in the event of a job loss by their household members. Although the difference is not very stark, there is some evidence that the survivor function for women exposed to a job loss of their household member is lower than that of men. Overall, the descriptive analysis presented seems to suggest that individuals, and women in particular, are less likely to remain in the same labour market state (i.e. survive) once their household members experienced a variation in their labour supply. We interpret this finding as confirming our hypothesis that labour supply is indeed one of the coping strategies used by the household to protect its members in the face of risk. In what follows, we use econometric models to test the statistical significance of these findings, controlling for a set of possible confounding variables.

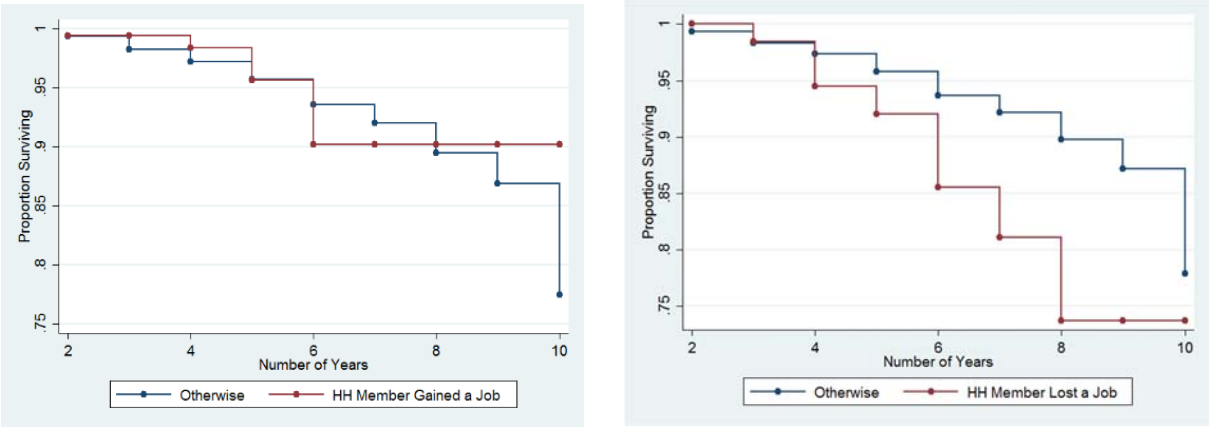

Figure 1: Kaplan-Meier survival estimates, using retrospective data

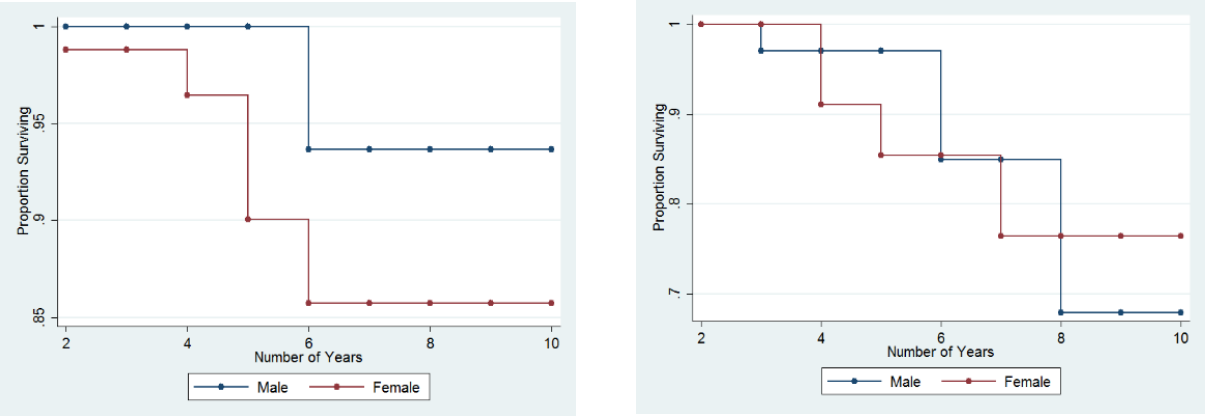

Figure 2: Kaplan-Meier survival estimates, by gender

Note: The graph on the left shows differences in Kaplan-Meier survival estimates by gender in the event a household member gained a job. Similarly, the graph on the right shows differences in Kaplan-Meier survival estimates by gender in the event a household member experienced a job loss.

5. Econometric results

5.1 Main results

In the first part of the analysis, we investigate whether individuals who are in households in which one of the members experience either a job gain or a job loss adjust their employment behaviour by transitioning from one labour market state to the other. We focus on two specific transitions: employment exits and entries.

In Table 3, we present the maximum likelihood estimates of Equation (4). Column (1) reports the probability of becoming non-employed and, in column (2), we report the probability of becoming employed.[14] Starting from column (1), the estimated coefficient implies that individuals are significantly more likely to exit employment in the event that one of their household members loses a job. To produce a meaningful interpretation of the parameters, one can exponentiate the coefficients to obtain the hazard ratios. For example, the estimated coefficient associated with a household member losing a job, $\emptyset$, becomes $\exp(1.346) = 3.841$ and implies that individuals whose household member lost a job have a probability of becoming non-employed that is approximately four times higher than that of their counterparts.[15]

Considering the estimated coefficients of the other covariates, as expected we find a negative effect of education on the probability of exiting employment (p-value = 0.105). This result implies that people with more education are less likely to become jobless. Furthermore, we can see a strong and positive effect of being female. In this case, the parameter associated with the dummy variable female captures the overall difference in the (conditional) probability of exiting from employment for women relative to men. In this case, the estimated coefficient is positive and statistically significant, implying that, on average, women are more likely to exit employment than men. We further observe a statistically significant effect of age on employment exit. The estimated results suggest that, as individuals grow older, the less likely they are to exit from employment. The estimated coefficient on the squared term suggests that this relationship is concave.

When we switch to column (2), we find that the effect of a household member experiencing a job gain has a positive and significant association with the probability of employment entry. Again, if we consider the hazard ratio, $\exp(0.816) = 2.262$, it implies that individuals whose household member gained a job have a probability of becoming employed that is approximately two times higher than that of their counterparts. Furthermore, the estimated results show a strong and positive association between schooling and employment entry, confirming that education is indeed a strong predictor of entering employment. The estimated coefficient for the female dummy variable in this case is significant and negative, entailing that women are less likely than men to become employed. Finally, the results suggest that the older individuals get, the more likely they are to enter into employment.

[14] Note: to ease the exposition we here use the word probability, but it is to be interpreted as a conditional probability, namely the hazard function.
[15] This was done in STATA by means of the *eform* command.

Table 3: Hazard estimates

	(1) Hazard of becoming non-employed	(2) Hazard of becoming employed
HH member gained job	0.372	0.816**
	(0.734)	(0.369)
HH member lost job	1.346**	0.349
	(0.590)	(0.721)
Covariates		
Years of schooling	-0.074	0.078**
	(0.046)	(0.036)
Father's years of schooling	0.040	0.015
	(0.052)	(0.024)
Mother's years of schooling	-0.022	0.010
	(0.046)	(0.027)
Household head (= 1)	-0.271	0.734
	(0.439)	(0.507)
Female	1.353***	-0.456*
	(0.403)	(0.261)
Age	-0.112**	0.199***
	(0.053)	(0.057)
Age squared	0.134**	-0.276***
	(0.068)	(0.080)
Experience	0.000	
	(0.046)	
Experience squared	-0.013	
	(0.085)	
Tenure	0.035	
	(0.057)	
HH enterprise (= 1)	-0.264	
	(0.307)	
Town dummies	X	X
Time dummies	X	X
Observations	6 483	1 568

Source: Tanzania Household Urban Panel Survey.

Note: The table presents mixed proportional hazard (MPH) estimates of exits out of and entries into employment. The results are conditional town dummies and baseline hazard dummies. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

So far, the results document that, as in a risk-sharing institution, individuals adjust their employment behaviour to compensate for variations in the labour supply of their household members by transitioning from one labour market state to another. This suggests that labour supply is indeed one of the coping strategies used by the household to cope with idiosyncratic risk. We next test for the hypothesis that women are more likely to respond to variations in the labour supply of their household members than men. To do this we simply use an interaction between the female dummy and the variables G_{it-1} and L_{it-1}.

Table 4 reports the estimated coefficients for this model. The results reported in column (1) suggest that, relative to men, women whose household members experienced a job loss have a statistically significant higher probability of exiting employment. In column (2), in contrast, the estimated coefficients imply that, on average, women are significantly more likely to enter employment in response to a job gain experienced by a household member. These results confirm our hypothesis that this coping strategy used by the household relies strongly on women's labour supply. In particular, our findings are in line with the work of Bhalotra and Umaña-Aponte (2010), who, even if using different types of shocks, conclude that insurance motives are likely to trigger the dynamics of women's employment behaviour. In particular, and consistent with our results, they find strong evidence of pro-cyclical labour supply behaviour for women in Africa and argue that the underlying

structure of families in Africa may explain the results. In what follows, we attempt to offer an explanation of our results.

Table 4: Hazard estimates

	(1) Hazard of becoming non-employed	(2) Hazard of becoming employed
HH member gained job * Female	0.686 (0.758)	0.894* (0.463)
HH member lost job * Female	1.778*** (0.621)	0.411 (1.142)
Covariates		
Years of schooling	-0.081* (0.048)	0.078 (0.050)
Father's years of schooling	0.034 (0.078)	0.016 (0.040)
Mother's years of schooling	-0.021 (0.066)	0.012 (0.026)
Household head (= 1)	-0.289 (0.518)	0.733 (1.340)
Female	1.207*** (0.436)	-0.501 (0.354)
Age	-0.106 (0.066)	0.203* (0.115)
Age squared	0.127 (0.081)	-0.282* (0.165)
Experience	-0.012 (0.056)	
Experience squared	0.011 (0.112)	
Tenure	0.043 (0.090)	
HH enterprise (= 1)	-0.253 (0.305)	
Town dummies	X	X
Time dummies	X	X
Observations	6 483	1 568

Source: Tanzania Household Urban Panel Survey.
Note: The table presents mixed proportional hazard (MPH) estimates of exits out of and entries into employment. The results are conditional town dummies and baseline hazard dummies. Robust Standard Errors in parenthesis. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

5.2 Discussion

Taken at face value, the findings presented here entail what the theory of the added worker effect (AWE) would predict. As mentioned in section 2, AWE theory predicts that, (a) if the husband suffers a job loss, the wife will be motivated to temporarily increase her labour supply to make up for the loss of income; and (b) once the husband finds a job, the wife will decrease her labour supply back to its original level. Our findings, in contrast, suggest a decrease in the labour supply of women in the event that a household member suffers a job loss and, in the event that a household member gains a job, we find an increase in women's labour supply. How can we reconcile the theory of the AWE with our findings?

Anecdotal evidence gathered during the data collection suggests that, in Tanzania, the household enterprise works as an unemployment insurance (UI) mechanism in that, when individuals lose their jobs in the labour market, they can rely on a position in the household enterprise, rather than staying idle and waiting for a new job. Further, it was reported that the burden of this UI is borne by women.

Specifically, given returns to specialisation, in the default scenario men would allocate their time in the labour market, while women would offer their labour supply either entirely to the household enterprise or combine both the household enterprise and housework. However, in the event that the (male) household member loses his job in the labour market, women would temporarily give up their position in the household enterprise and move out of the labour force, i.e. become inactive, to dedicate their labour to housework. Vice versa, women would take over the household enterprise when the (male) household member finds a job in the labour market. This type of story is consistent with the summary statistics showed above. In particular, Table 2 documents that, while women are significantly more likely than men to transition into and out of employment, men are more likely to transit between job types, that is from a wage job to the household enterprise and vice versa.

One way to further test this theory is to estimate a number of (destination-specific) mixed proportional-hazard models for the sample of women only. In particular, we would expect women to transition from the household enterprise to inactivity in the event that a household member loses a wage job. Conversely, if a household member gains a wage job we would expect women to exit inactivity and enter the household enterprise.[16] Table 5 reports the results of this exercise and confirms our hypothesis. In column (1), the estimated coefficient, although statistically insignificant, entails that, when a household member loses a wage job, women are more likely to transition from the household enterprise to inactivity. The estimated coefficient reported in column (2) is positive and strongly significant, implying that, when a household member gains a wage job, women are more likely to increase their labour supply and move from inactivity to the household enterprise. We interpret this findings as suggestive, although not conclusive, evidence of the key role played by the household enterprise as a buffer sector through which individuals share risk with their household members.

5.3 Robustness checks

We subjected our findings to two main robustness checks that we discuss in what follows. First, one can argue the estimated results to be driven by town-specific trends, either upturns or downturns, which might have caused both the change in labour supply experienced by the household member and the associated change in employment behaviour. To address this issue, we add to the baseline model a set of variables interacting town and time dummies and find our results to be consistent. This allows us to rule out that the observed variations and responses in individuals' labour supply are caused by town-specific trend and shocks. Tables 6 and 7 show that our results are robust to this check.

[16] Ideally, we would like to estimate these models by focusing on changes in the labour supply of male household members, but our sample size is not large enough to perform this exercise.

Table 5: Hazard estimates for women

	(1) Transition from HH enterprise to inactivity	(2) Transition from inactivity to HH enterprise
HH member gained wage job		2.857*** (0.264)
HH member lost wage job	0.047 (1.017)	
Covariates		
Years of schooling	-0.024 (0.065)	0.022 (0.045)
Father's years of schooling	0.038 (0.046)	0.035 (0.032)
Mother's years of schooling	0.012 (0.048)	-0.009 (0.036)
Household head (= 1)	-0.112 (0.590)	1.409** (0.551)
Age	-0.138** (0.067)	0.164** (0.064)
Age squared	0.198** (0.089)	-0.192** (0.084)
Experience	-0.056 (0.077)	
Experience squared	0.047 (0.153)	
Tenure	0.080 (0.077)	
Town dummies	X	X
Time dummies	X	X
Observations	1 678	1 267

Source: Tanzania Household Urban Panel Survey.

Note: The table presents mixed proportional hazard (MPH) estimates of exits out of and entries into employment. The results are conditional town dummies and baseline hazard dummies. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

Table 6: Hazard estimates, town-specific trends

	(1) Hazard of becoming non-employed	(2) Hazard of becoming employed
HH member gained job	0.393 (0.736)	0.808** (0.386)
HH member lost job	1.336** (0.607)	0.357 (1.072)
Covariates		
Years of schooling	-0.080* (0.046)	0.078 (0.073)
Father's years of schooling	0.033 (0.068)	0.014 (0.069)
Mother's years of schooling	-0.019 (0.058)	0.011 (0.026)
Household head (= 1)	-0.253 (0.504)	0.728 (2.448)
Female	1.340*** (0.408)	-0.445 (0.506)
Age	-0.107* (0.060)	0.200 (0.213)
Age squared	0.128* (0.076)	-0.277 (0.303)
Experience	-0.013 (0.053)	
Experience squared	0.014 (0.107)	
Tenure	0.041 (0.081)	
HH enterprise (= 1)	-0.256 (0.306)	
Town dummies	X	X
Time dummies	X	X
Interaction of town and time dummies	X	X
Observations	6 483	1 568

Source: Tanzania Household Urban Panel Survey.

Note: The table presents mixed proportional hazard (MPH) estimates of exits out of and entries into employment. The results are conditional town dummies and baseline hazard dummies. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

Table 7: Hazard estimates, town-specific trends

	(1) Hazard of becoming non-employed	(2) Hazard of becoming employed
HH member gained job * Female	0.686	0.894*
	(0.758)	(0.463)
HH member lost job * Female	1.778***	0.411
	(0.621)	(1.142)
Covariates		
Years of schooling	-0.081*	0.078
	(0.048)	(0.050)
Father's years of schooling	0.034	0.016
	(0.078)	(0.040)
Mother's years of schooling	-0.021	0.012
	(0.066)	(0.026)
Household head (= 1)	-0.289	0.733
	(0.518)	(1.340)
Female	1.207***	-0.501
	(0.436)	(0.354)
Age	-0.106	0.203*
	(0.066)	(0.115)
Age squared	0.127	-0.282*
	(0.081)	(0.165)
Experience	-0.012	
	(0.056)	
Experience squared	0.011	
	(0.112)	
Tenure	0.043	
	(0.090)	
HH enterprise (= 1)	-0.253	
	(0.305)	
Town dummies	X	X
Time dummies	X	X
Interaction of town and time dummies	X	X
Observations	6 483	1 568

Source: Tanzania Household Urban Panel Survey.

Note: The table presents mixed proportional hazard (MPH) estimates of exits out of and entries into employment. The results are conditional town dummies and baseline hazard dummies. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

Another potential concern about the validity of our findings is that the analysis presented is based on recall data. Although this feature is the main strength of our data, since it allows us to follow individuals through their entire employment history, it is important to assess whether the evidence we find is reliable and not a mere artefact of erroneous memories. In order to account for this potential issue, we ran the various regressions as a robustness check, but only took into consideration the most recent 25 years of recall data. Tables 8 and 9 show the results of this exercise. Even though this robustness check entails a considerable reduction in the number of spells, the results remain virtually unchanged.

Table 8: Hazard estimates, recall bias

	(1) Hazard of becoming non-employed	(2) Hazard of becoming employed
HH member gained job	0.468 (0.731)	0.801** (0.375)
HH member lost job	1.425** (0.583)	0.229 (0.866)
Covariates		
Years of schooling	-0.056 (0.046)	0.051 (0.039)
Father's years of schooling	0.044 (0.042)	0.014 (0.038)
Mother's years of schooling	-0.040 (0.039)	0.006 (0.026)
Household head (= 1)	-0.190 (0.415)	0.702 (1.438)
Female	1.289*** (0.402)	-0.447 (0.317)
Age	-0.110** (0.055)	0.193* (0.103)
Age squared	0.137** (0.069)	-0.272* (0.149)
Experience	0.004 (0.047)	
Experience squared	-0.026 (0.090)	
Tenure	0.035 (0.045)	
HH enterprise	-0.208 (0.322)	
Town dummies	X	X
Time dummies	X	X
Observations	5 950	1 370

Source: Tanzania Household Urban Panel Survey.

Note: The table presents mixed proportional hazard (MPH) estimates of exits out of and entries into employment. The results are conditional town dummies and baseline hazard dummies. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

Table 9: Hazard estimates, recall bias

	(1) Hazard of becoming non-employed	(2) Hazard of becoming employed
HH member gained job * Female	0.820	0.877**
	(0.748)	(0.439)
HH member lost job * Female	1.896***	0.269
	(0.574)	(1.083)
Covariates		
Years of schooling	-0.058	0.051
	(0.046)	(0.037)
Father's years of schooling	0.045	0.016
	(0.043)	(0.029)
Mother's years of schooling	-0.042	0.006
	(0.039)	(0.026)
Household head (= 1)	-0.228	0.715
	(0.420)	(0.983)
Female	1.136***	-0.495*
	(0.409)	(0.286)
Age	-0.109**	0.196**
	(0.055)	(0.076)
Age squared	0.136*	-0.277**
	(0.070)	(0.109)
Experience	0.006	
	(0.048)	
Experience squared	-0.030	
	(0.092)	
Tenure	0.036	
	(0.046)	
HH enterprise (= 1)	-0.212	
	(0.317)	
Town dummies	X	X
Time dummies	X	X
Observations	5 950	1 370

Source: Tanzania Household Urban Panel Survey.

Note: The table presents mixed proportional hazard (MPH) estimates of exits out of and entries into employment. The results are conditional town dummies and baseline hazard dummies. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

6. Conclusions

Individuals living in developing countries are often faced with extreme conditions in their day-to-day life. Given their low level of income and the absence of social security nets, individuals have to rely on each other to cope with these conditions. In this study we specifically investigate the role played by individuals' labour supply as a coping strategy used by the household. Our hypothesis is that, as in a risk-sharing institution, individuals adjust their employment behaviour in response to variations in labour supply experienced by their household members. We exploit a unique dataset of employment histories of urban households in Tanzania to test this hypothesis.

We find evidence that, in the context of developing countries, the household works as a risk-sharing institution built around women's labour supply. Specifically, we find that individuals, and women in particular, adjust their employment behaviour in response to either a job gain or job loss experienced by their household members. In particular, women tend to decrease their labour supply in response to a job loss suffered by a household member and, conversely, they increase their labour supply in the event that a household member gains a job. These findings are in line with the study by Bhalotra *et al*. (2010).

Finally, we developed and tested a simple theory of labour-supply decisions to reconcile our findings with existing theories of intra-familial labour supply. The key insight of the theory is that the household enterprise works as an unemployment insurance mechanism in the context of developing countries, in that individuals who lose their jobs can rely on and offer their labour supply in the household enterprise, rather than remaining idle and waiting for a new job. Unfortunately, data availability only permitted suggestive, rather than conclusive, evidence for this theory. Indeed, one potential drawback of recall data is that people may fail to report short and temporary spells of joblessness, as they do not think these are worth mentioning. However, these short and temporary spells are exactly what we would need to fully test this theory.

An implication of this study is that individuals may not always choose their labour supply behaviour according to their skills, education and ambition, but rather according to the needs of their family members. From a policy perspective, a potential consequence of this behaviour is the inefficient allocation of human resources in the labour market. It is likely that individuals might give up their education and job training programmes in the case that one of their household members experiences a labour market shock. The key for successful policy implications to tackle this issue is a deep understanding of the nature of the different coping mechanisms of households. Since this is a case of market failure, it is likely that the creation of formal safety nets might increase the overall efficiency and well-being in society. Moreover, the policy implications implied by our findings may favour women relative to men, since women are affected more by shocks experienced by their household members. Finally, drawing from anecdotal evidence gathered during data collection, we put forward in this paper the hypothesis that the household enterprise is at the core of risk sharing amongst household members. Future research should investigate the functioning of the household enterprise and its role in economic development. The outcomes of these investigations are fundamental for assessing which direction policy interventions should take.

References

Abbring J & Van der Berg G, 2003. The identifiability of the mixed proportional hazards competing risks model. Journal of the Royal Statistical Society 65(3): 701–10.

Ashenfelter O & Heckman J, 1974. The estimation of income and substitution effects in a model of family labor supply. Econometrica 42(1): 73–85.

Attanasio O, Low H & Sanchez-Marcos V, 2005. Female labor supply as insurance against idiosyncratic risk. Journal of the European Economic Association 3(2/3): 755–64.

Bhalotra S & Umaña-Aponte M, 2010. The dynamics of women's labour supply in developing countries. IZA Discussion Paper no 4879. IZA, Bonn, Germany.

Deaton A, 1991. Savings and liquidity constraints. Econometrica 59(5): 1221–48.

Deaton A, 1997. The analysis of household surveys: A microeconometric approach to development policy. Washington DC: World Bank Publications.

Dercon S & Krishnan P, 2000. In sickness and in health: Risk sharing within households in rural Ethiopia. Journal of Political Economy 108(4): 688–727.

Fafchamps BYM & Lund S, 2003. Risk-sharing networks in rural Philippines. Journal of Development Economics 71(2): 261–87.

Heckman JJ & Macurdy TE, 1980. A life cycle model of female labour supply. The Review of Economic Studies 47(1): 47–74.

Jenkins SP, 1995. Easy estimation methods for discrete-time duration models. Oxford Bulletin of Economics and Statistics 57(1): 129–36.

Jenkins SP, 2005. Survival analysis. Unpublished notes. Institute for Social and Economic Research, University of Essex, Colchester UK. Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.176.7572&rep=rep1&type=pdf (Accessed 3 May 2018).

Lundberg SJ, 1985. The added worker effect. Journal of Labor Economics 3(1): 11–37.

Mace B, 1991. Full insurance in the presence of aggregate uncertainty. Journal of Political Economy 99(5): 928–56.

Mincer J, 1962. Labor force participation of married women: A study of labor supply. In National Bureau of Economic Research (ed), Aspects of labor economics. Princeton: Princeton University Press.

Morduch J, 1991. Consumption smoothing across space: Tests for village-level responses to risk. Harvard University (mimeograph).

Nicoletti C & Rondinelli C, 2010. The (mis)specification of discrete duration models with unobserved heterogeneity: A Monte Carlo study. Journal of Econometrics 159(1): 1–13.

Prentice RL & Gloeckler LA, 1978. Regression analysis of grouped survival data with application to breast cancer data. Biometrics 34(1): 57–67.

Rosenzweig MR, 1988. Risk, implicit contracts and the family in rural areas of low income countries. Economic Journal 98(393): 1148–70.

Skoufias E & Parker SW, 2002. Labor market shocks and their impacts on work and schooling: Evidence from urban Mexico. FCND Discussion Paper No 129. Washington DC: International Food Policy Research Institute.

Townsend R, 1993. Intra-regional risk-sharing in Thailand, an uneven but growing economy. Washington DC: Institute for Policy Reform

Townsend R, 1994. Risk and insurance in village India. Econometrica 62(3): 539–91.

Udry C, 1994. Risk and insurance in a rural credit market: An empirical investigation in Northern Nigeria. Review of Economic Studies 61(3): 495–526.