Spatial Dimensions of Unemployment

Martin Wittenberg*
School of Economic and Business Sciences
University of the Witwatersrand
South Africa

We investigate the correlates of unemployment by means of large cross-sectional data sets. We argue that there is evidence that access to employment is mediated through household and neighbourhood networks. The effect of these networks is to structure the South African labour market along urban insider- rural outsider lines. The implication of the analysis is that job creation by itself is unlikely to alleviate all of the unemployment problem, since new jobs are likely to go disproportionately to people who are better positioned to access those jobs.

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South Africa's high measured unemployment rate has now been a cause of concern for a number of years. The simplest labour market models would assume that this is purely a pricing issue: that either the reservation wages of the unemployed are too high (in which case the unemployment is of the voluntary type), or that the wage is not at a market clearing level, due to various distortions in the South African economy.

This simple model of the labour market is predicated on two assumptions: job search is frictionless and costless and that individuals operate purely on market signals, i.e. that there are no forms of "non-market interactions" (Glaeser and Scheinkman 2000) in the labour market. Nevertheless there is now a vast body of theoretical and empirical work which shows that these assumptions are at least questionable. This of course does not invalidate the importance of prices, but it does suggest that a more nuanced picture is required.

1 Search and labour market flows

1.1 Theoretical perspectives

The basic framework of the search approach to labour market interactions is well reviewed in a number of places (see for example Devine and Kiefer (1991), Mortensen and Pissarides (1999)). The basic insight is that there are intrinsic search frictions which will prevent market clearing in the short run, even with arbitrarily large shifts in prices. These search frictions involve asymmetries of information (a potential worker may not read the newspaper in which a job is advertised), screening costs and the fact that any contract needs to bring the potential worker and the firm into spatial and temporal proximity[1].

Given that search takes time and involves cost, it can be seen as a form of investment. Search costs are incurred now, in the hope of a pay-off in the future. One of the implications of this, is that workers should not always take the first job that becomes available, since the value of that job may be lower than the opportunity cost - the potential gain from getting a much better job later. Implicit in this is, of course, the assumption that jobs are not be created equal: that the same worker in a different job may get better remunerated. The reasons for this heterogeneity is often modelled as

[1] This is true even if the worker communicates with the firm via e-mail.

arising out of match-specific productivities, that the "chemistry" between some firms and some workers just makes for a more productive match than would otherwise be the case. For similar reasons, firms should not always hire the first worker that presents herself.

It can be shown that with these assumptions workers should operate with a "reservation wage" policy, except that the reservation wage should be set not just to cover the cost of the leisure foregone, but also the opportunity cost of foregoing additional search. Taking a job (or hiring a worker) is a little like incurring sunk costs. The extent of these costs will determine how easy it is for either one of the parties to break the match. In turn it will determine how willing the parties are to enter into the contract in the first place.

One of the important impacts of search theory is that it has refocused attention away from "stock" concepts such as the number of unemployed to "flow" measures, i.e. the transition rates between states[2]. From the point of search theory, an unemployed person should always be thought of as being in transition: either into a job or out of the labour market. The key question is really the rate at which these transitions happen. In Figure 1 we have indicated some of the major flows that we would wish to focus on. We have also indicated (by means of a broken line) that the transition from not searching to searching (and vice versa) is not necessarily a discontinuous one: there may be different search intensities between different people (a model with endogenous search intensity is given in Pissarides 2000, Chapter 5). What determines whether someone is searching or takes up a job offer is essentially a comparison of the relevant capitalised values: of being in a job, of searching, or of engaging in other activities.

This model can be explored in a general equilibrium fashion. Pissarides (2000), for example, provides a model of job creation/job destruction, in which even the state of working becomes transitional. Schumpeterian "creative destruction" ensures that the productivity of any particular job match will eventually come to an end. The empirical evidence for the relevance of such a framework is provided by the work of Davis, Haltiwanger and Schuh (1996) which suggests that turnover of jobs in the U.S. economy is very large indeed.

In this general equilibrium framework it becomes clear that the steady-

[2] Of course a focus on the rates can also allows us to recover the equilibrium level of the stocks.

state stocks of individuals in each category become a function of all the parameters determining all flows. This should immediately give us some pause for thought, since the kind of analysis that we will be conducting in this paper is really a partial equilibrium one - considering what we might infer about the nature of the flows from the supply side. A further limitation is that we will be considering essentially a static picture, which is somewhat paradoxical for a paper concerned with transitions.

1.2 An initial look at the "flows"

In Figure 2 (taken from Wittenberg (1999a)) we have graphed the proportion of each age group working, unemployed and searching, unemployed and not searching and not economically active. The transitions in these proportions from age group to age group give us a sense of the direction and magnitude of the flows that occur for people during that year. Of course these are unbiased estimates of the flow rates only if the economy is in a long-run equilibrium: so that the experiences of older workers are an unbiased estimate of the experiences of young workers in the future. Nevertheless these notional flows are useful in that they indicate some of the pressures that are being experienced in different parts of the labour market.

1.2.1 The transition from "not economically active" to "economically active"

It is clear that the transition from the school system to the world of work takes much longer, on average, for African males than for members of the other race groups. In their mid-twenties thirty to forty percent of African males are still classified as "not economically active". The net flows out of this category only cease at about age thirty.

1.2.2 The transition into work

It is clear that the transition into work is also much slower. Furthermore the flow into work is slower than the flow out of the schooling system. As a result one sees a build up in the proportion of the unemployed (whether searching or not). The highest levels of unemployment are recorded around age 27.

The net flow rates into employment slow markedly after age thirty and reach zero at about age forty.

1.2.3 The transition out of unemployment

It is clear that part of the decline in the levels of unemployment recorded after age 27 is due to the fact that people are still being absorbed into work. Nevertheless the fact that unemployment continues to decline even after age forty (when there are no net additions to the workforce) suggests that some of the unemployed who are searching cease to do so. Indeed it is possible to see an upturn in the proportion not economically active after age forty. The proportions go up from about 10% to 15% by age fifty. Furthermore the noticeable levelling off in those considered unemployed on the expanded definition, suggests that some of those who were actively searching have changed their search intensity. Indeed, as Figure 3 suggests (again from Wittenberg (1999a)), there is some drop off in search intensity with age. What is perhaps remarkable about this figure is that this decline is not more marked. One would assume that discouragement would follow from lack of success in search activities. This diagram suggests that some people continue to search even if they have had a sequence of failures in the past. The converse of course also applies: some people never seem to start searching.

This suggests that it is perhaps misleading to refer to the "expanded" unemployed as discouraged workseekers if discouragement is intended to refer to the result of personal experiences. It seems more likely that "discouragement" is a community phenomenon - that entire groups of young people convince each other that there are no jobs to be had. The lack of success of individuals who might be searching becomes the lesson for everyone else not to even bother. If true, such a phenomenon would be very important, since unemployment might become self-perpetuating. On the other hand, if one or two people within such a community have success, it might lead to rather large-scale changes in the aggregate intensity of search. We will devote more attention to

1.2.4 The transition from work to retirement

It is clear that African males start retiring slightly later than Coloured and White males. The proportions left in employment are similar after age 55.

1.3 The "flows" in spatial context

In Figure 4 (from Wittenberg (1999a)) we have placed some of these flows into a spatial context. It is clear that employment and search activity is higher in urban areas, while the proportion of those not economically active or who are not searching is higher in the rural areas. The higher search pattern in the urban areas is consistent with the idea that the value of search is higher there - which would be a function not only of the probability of finding a job, but also the value of the job, once found.

2 The importance of social interactions

We have suggested above that the choice by an individual whether or not to become active in the labour market may be mediated by the experiences of other individuals. In particular, we would expect the context of the household to be important. Indeed, the structure of the household will have an impact on all the variables involved in the decision: the value of finding a job, the cost of searching as well as the value of non-market activities.

The importance of this balancing of job search with other activities within the household has been recognised at least since the work of Becker (Becker 1965, Becker 1991). One implication of this is that some household members may condition their decisions on the success or failure of other members to find employment. This is known in the literature as the "added worker effect" (Lundberg 1985). It may lead to particular kinds of unemployment traps, where an increase in unemployment may, perversely, lead to greater labour supply, aggravating the problem (Basu, Genicot and Stiglitz 1998)

Other household effects have also been recognised. Households may provide the necessary resources for some people to engage in job search. These resources can be financial or effort in non-market activities. For instance if there is another adult woman in the house, it may make it easier for a woman with young children to reenter the labour force. Alternatively income accruing to other family members may allow some individuals to withdraw from the labour market. Bertrand, Miller and Mullainathan (2000) suggest that pension income in South Africa has been used to support the "leisure" of certain other male members of the household.

In a previous paper (Wittenberg 1999a) I suggested that employed members of households may provide crucial labour market information to other individuals. This "network" effect would tend to offset the "added worker" effect, or at least, it would suggest that individuals who do engage in search from households where there is already someone employed would have an advantage in finding employment.

Finally there is the possibility of a "work culture" effect - that in households (and communities) where there is a history of working, individuals are expected to show effort in finding employment, while perhaps in communities where there is a more patchy history of work, it is not anticipated that job search will be successful, so effort is lower. This might explain the relatively constant proportion of searchers within the unemployed population, noted in the discussion above.

2.1 Types of social effects

In many explanations of South Africa's high unemployment rate, social effects such as those noted above are cited. Klasen and Woolard, for instance, have suggested that pension payments may explain some of the spatial mismatches between labour demand and supply (1998). Redistribution within the household may account for high reservation wages. I have previously argued that the importance of access to the labour market may be producing an insider-outsider structure in South African labour markets (1999a)

It would be useful to explore some of these issues more rigorously. In order to do this we draw on Manski's work on the "reflection problem" (Manski 1993, Manski 1995). Manski distinguishes between three kinds of "effects":

- correlated effects

  These arise when certain unmeasured attributes of individuals are important for the outcome, and are correlated within the group. An example might be ability. Ability would certainly affect an individual's probability of finding employment and would therfore affect the measured labour market outcomes. If ability is clustered within families, we would observe some households with many individuals working and others with much fewer. Correlated effects are really non-social effects, which masquerade as social effects.

- contextual effects

  These exist when the outcome in question depends on the particular context provided by the group. For instance, the average income in the household may matter if search costs have to be financed. Similarly the average level of literacy in the household may be important in gaining access to information about job opportunities. The pension effect referred to above is an example of contextual effects - it is income which matters, not the household *per se*, but income is mediated by the existing household structure. The "network" effect could also be interpreted as a contextual effect, if it is information only that matters. If networks are themselves conduits for hiring, then this would be an example of an endogenous effect (considered below).

- endogenous effects

  In the case of endogenous effects, group membership matters in a fundamental way. Members of groups adapt their behaviour and aspirations to the prevailing group norms, so different individuals affect each other's outcomes directly - not just through the context they provide for each other. The importance of such group effects has become an area of active research (Case and Katz 1991, Glaeser and Scheinkman 2000, Becker and Murphy 2000, Katz, Kling and Liebman 2001, Sacerdote 2001). It is thought to be particularly important in analysing the extent of crime (Glaeser, Sacerdote and Scheinkman 1996, Glaeser and Sacerdote 1999). In our context such effects would exist if there is a "work culture" or "collective discouragement" effect.

We can capture these differences by means of the following model:

$$\begin{aligned} y_{ij} &= x_{ij}^{/}\beta + \gamma E\left(y|h_i\right) + \phi E\left(c|h_i\right) + u_{ij} \\ u_{ij} &= a_{ij} + \varepsilon_{ij}, \text{ with } cov\left(a_{ij}, a_{ik}|h_i\right) \neq 0 \end{aligned} \tag{1}$$

Here y_{ij} is the outcome we are interested in for individual j in group (household) i, x_{ij} is a set of individual explanatory variables, h_i is the variable(s) defining group membership, c is a set of variables that capture the context and u_{ij} represents everything that we cannot measure. We break this down into a set of attributes a_{ij} that are correlated within the group and a set of idiosyncratic errors.

If the coefficient γ is non-zero, then we have endogenous social effects present. If ϕ is non-zero, then we have contextual effects, while if α_{ij} is non-zero, then we have correlated effects. Note that we could have all types of effects operating simultaneously. Unfortunately if this is the case, then it becomes almost impossible to identify the different types of effects.

2.2 Identification and estimation problems

As Manski has noted, with the linear formulation of equation 1, we immediately have an identification problem, since taking the expectation with respect to h

$$E\left(y|h_i, x_{ij}\right) = x_{ij}^{/}\beta + \gamma E\left(y|h_i\right) + \phi E\left(c|h_i\right) + E\left(u_{ij}\right)$$

i.e.

$$E\left(y|h_i\right) = \frac{1}{1-\gamma}\left(E\left(x_{ij}^{/}\right)\beta + \phi E\left(c|h_i\right) + E\left(u_{ij}\right)\right) \tag{2}$$

so that $E\left(y|h_i\right)$ becomes collinear with the contextual effects and the individual level explanatory variables. We would therefore need additional identifying assumptions or information in order to separate out the different kinds of effects.

In the context of dummy dependent variables we face additional problems. We might wish to model this case (by analogy with equation 1) in a latent variable framework as

$$\begin{aligned} y_{ij}^{*} &= x_{ij}^{/}\beta + \gamma E\left(y|h_i\right) + \phi E\left(c|h_i\right) + u_{ij} \\ u_{ij} &= a_{ij} + \varepsilon_{ij}, \text{ with } cov\left(a_{ij}, a_{ik}|h_i\right) \neq 0 \\ y_{ij} &= 1 \text{ if, and only if, } y_{ij}^{*} > 0 \end{aligned} \tag{3}$$

We immediately face the problem of how to interpret the explanatory variable $E\left(y|h_i\right)$ - do we think that it is the actual outcomes that affect the latent variable, or is it the latent variables of other members of the group? In our context, is it the actual achieved outcomes of employment that "rubs off" on other members of the group, or is it the attitude towards work or the intensity of search?

If we think that it is actual outcomes that matter (as in the network story), then the model in 3 is actually logically inconsistent. Maddala (1983, Section 5.7) notes that such models logically require γ to be zero. Intuitively this makes sense: actual outcomes should not determine the propensity to achieve that outcome![3]

There are two ways around this problem. Firstly, we might try to impose some structure on the direction of the flows. If we can plausibly identify some

[3] Regrettably this vitiates some of my work done in the past (Wittenberg 1999c, Wittenberg 1999b).

individuals as achieving work prior to the others, then we can condition the probabilities of subsequent individuals of gaining employment on the outcomes of the previous members of the group. This really requires panel data, although in some of our regressions we use age as a proxy for the direction of social influence. In this case our model is

$$y_{ij}^{*} = x_{ij}^{\prime}\beta + \gamma E_{k<j}\left(y_{ik}|h_i\right) + \phi E\left(c|h_i\right) + u_{ij} \qquad (4)$$

where we have ordered individuals from oldest to youngest. Note that estimating this model with standard techniques will still be problematic if there is any correlation in the errors (as there is likely to be).

Secondly, we could interpret the social effects as operating through the latent variables rather than the actual outcomes. We are then back in the original framework of Manski and the best that we can then do is to estimate the reduced form of the model (equation 2). We can get some idea of the importance of "social effects" by examining the coefficients of contextual variables. In practice we will also introduce household level (fixed or random) effects α_i to capture both correlated effects and any other contextual effects that we have not been able to measure. We therefore assume that the reduced form of the model will be

$$y_{ij}^{*} = x_{ij}^{\prime}\beta + \overline{x}_{ij}^{\prime}\beta^{*} + \phi^{*}E\left(c|h_i\right) + \alpha_i + \varepsilon_{ij} \qquad (5)$$

If we could plausibly argue that some variables in x_{ij} do not operate as contextual variables but are purely proxies for the endogenous effect, we could use the coefficient on $\overline{x}_{ij}^{\prime}$ to infer the size of γ (since $\beta^{*} = \frac{\beta}{1-\gamma}$). This amounts to indirect least squares/instrumental variables, using the explanatory variables of other individuals to infer the size of their impact on the outcome of the individual in question (this is essentially the approach of Case and Katz 1991). Unfortunately it is very hard to make the case that variables that have a direct impact on outcomes (such as education) do not also have contextual effects.

Given these problems, we content ourselves with examining the size of contextual effects, as well as with the proportion of the overall variance contributed by the non-idiosyncratic "group" effect.

2.3 Method of estimation

We present both linear probability and logit model estimates. We do so for the sample overall (Table 3), for the urban areas only (Table 4) and for the rural areas (Table 5). The data set that we use is the 1995 October Household Survey. Note that in all cases we compare the probability of working to all other states, i.e. searching or being out of the labour force. Since searching behaviour is likely to depend on the probability of finding work (by the arguments made above), this seems to be a cleaner comparison.

We use a linear probability specification initially, since it lends itself to easy interpretation and can be more readily extended to contexts with more complicated specifications with larger data sets[4]. In particular, we estimate equation 4 by means of OLS, correcting for within cluster correlation. More specifically we model it as

$$y_{ij}^* = x_{ij}^{\prime}\beta + \gamma \sum_{k<j} y_{ij} + \phi E\left(c|h_i\right) + u_{ij}$$

This implies that the benefits of contacts are cumulative - additional people who work within the household are able to bring in additional information. The results of this model are reported in column (1) in Tables 3, 4 and 5. This model will produce unbiased coefficients only if there is no household level effect, i.e. only if $\alpha_i = 0$.

The rest of the estimates rely on the reduced form specification of equation 5. In column (2) of the tables, we report fixed effects estimates. We use the resultant coefficients to estimate the proportion of the overall variance contributed by the household level factors. Since the fixed effects model also excludes all the contextual effects, this is an estimate of the total importance of contextual and correlated effects versus idiosyncratic effects.

Note that the standard formula used by regression packages to calculate this statistic does not work in this case, since the error terms do not all have the same variance. In the appendix we discuss how to extend the standard framework to the case of the linear probability model. In the appendix we also present a method by which a random effects model might be estimated. Unfortunately the empirical application of this method has thus far proved to be unstable. The reasons for this seem to be twofold: firstly the linear probability model is prone to giving point estimates that lie outside the valid range. This is not critical when estimates for the aggregate are desired, but seems to become more problematic when the relevant estimates "within" a household are to be calculated. Secondly, the generalised differencing that

[4] We do not report these results here. Some earlier versions are contained in an unpublished report (Wittenberg 1999b)

is required within households seems to reduce the variation available to give precise estimates. As a result some variables get dropped due to collinearity.

These sorts of problems prompt the use of models more specifically designed for dummy variables. In column (3) we use the conditional fixed effects estimator of Chamberlain (Greene 1997, pp.899–901). Since this estimator conditions on groups which have both positive and negative outcomes, it is not possible to compare this directly with the other estimates. In particular the fixed effects are conditioned out and so no estimate of the variance due to them is possible. In column (4) we estimate a random effects logit model (this is the extension of the random effects probit estimator to the logit case Greene 1997, p.896—899). This again allows us to recover an estimate of the relative importance of the social effects: although in this case we also have separate estimates of the contextual effects. The ρ reported here is therefore of the variance of α_i relative to the total error variance $(\alpha_i + \varepsilon_{ij})$.

2.4 Specification

We use gender of the individual, the highest education completed (in years) and a quadratic in age as our individual level variables. The contextual variables are given by a set of household compositional variables, as well as the average level of education among adults in the household (defined as people 15 and older) and the number of adults themselves.

For the compositional variables, we have calculated the proportion of the overall household that is a male infant (age $<=6$), a male child ($6<\text{age}<15$), male youth ($15\leq\text{age}<30$), male adult ($30\leq\text{age}<60$) and an old male ($\text{age}\geq 60$). The female categories are defined analogously. Adult females are the excluded category, so all coefficients should be interpreted as an increase in the relevant category with a concomitant decrease in the proportion of adult females. We are therefore considering the substitution of one type of member for another.

In all cases we estimate the coefficients for men and women within one model, but fully interacted, to allow the coefficients to differ by gender. This procedure does, however, restrict the idiosyncratic error process to be the same for men and women. Note that the standard errors in the regressions for men are actually for the slope dummy (i.e. for the difference between the two coefficients). We restrict the sample to African people only.

3 Results

3.1 Individual effects

The individual level variables are generally all significant, although the education variables show a rather small magnitude, particularly when men are considered. Undoubtedly part of the explanation is the crude way in which education has been included in the regressions. A more flexible functional specification would show that education beyond matric matters a great deal (Wittenberg 1999a).

The age and age^2 variables also behave as expected, with the probability of working increasing, but at a decreasing rate and eventually reaching a turning point somewhere in mid-life (44.6 years for men and 44.2 years for women in Table 3).

3.2 Spillover effects

If we consider the "simple" specification of column (1) it is clear that having an older member in the household who is employed has a statistically significant impact on the probability of finding work oneself. Given a baseline probability of being employed of 42.8% (for men) and 24.2% (for African women), this amounts to an increase in the probability of being employed in excess of 5% (men) and 10% (women).

Significantly, however, the spillovers are markedly different in urban and in rural areas. In urban areas, there is no statistically significant relationship, while the relationship is twice as strong in the rural areas.

This is the first indication that social effects in relationship to employment are more significant in rural areas than in urban areas.

3.3 Contextual effects

If we consider columns (2), it is clear that the overall importance of social effects (including the within household compositional effects) are very important relative to the idiosyncratic effects, once gender education and age have been controlled for. Around 40% of the remaining variation is contributed by household effects. Again this is somewhat larger in the rural areas than in the urban areas.

When we examine the pattern of the individual coefficients (in columns (1) and (4)), it is quite striking how much they seem to matter. The pattern of the coefficients is entirely plausible and quite gender specific. Increases in the proportion of infants and young children have a large negative effect on the probability of women working. Having older men around also has a negative effect on labour supply. This can be explained in terms of gender roles within the household (along Beckerian lines). The much larger coefficient associated with old men could be due either to greater nursing requirements, or it could be a straight income effect from the social pension. Comparing the urban and the rural coefficients, we note that there is some evidence that urban women go back to work after child birth, whereas this does not seem to be the case in the rural areas.

Interestingly enough, the average education level does not seem to matter much, it is significant only in Tables 4 and 5 for women: and then with opposite signs.

3.4 Unmeasured social effects

From column (4) we note that effects which are common within households but which haven't been captured by the contextual effects account for roughly a quarter of the remaining variation. These would include any correlated effects as well as any other contextual effects that we have not been able to measure.

Significantly, there is a large difference in the importance of these effects between rural and urban areas. In rural areas, household effects contribute a third to the overall variation.

Although it is not really permissible to do so, (since the estimates come from different models) we can deduce from the ρ coefficients in columns (2) and (4) how important the measured contextual effects are relative to the unmeasured ones. We find that for the sample as a whole the variance of the unmeasured social effects are roughly 35% of individual variation, while the sum of the variance of the measured and unmeasured social effects is 72%. Hence it appears that measured and unmeasured effects are of the same order of importance.

When we do analogous calculations for the urban and the rural areas, however, we find a very different picture. In the case of the urban areas the measured social effects seem about three times as important as the unmeasured effects, while in the rural areas, the unmeasured effects seem 66% more important.

4 Conclusions and policy implications

The key finding of this paper is that there seem to be strong social effects operating at the household level which mediate the success of different individuals in the labour market. To put it crudely, some households are more successful in getting their members employed than others. Some of these differences may be due to measurement problems. Perhaps correlated effects can account for most of these, in which case there would be few policy implications, other than the obvious ones, of improving education and paying attention to the other activities that generate value within the household.

The systematic differences in the strength of these social effects between urban and rural areas (as evidenced also by the "spillover" variable) suggest that there may be other forces at play here and that in some meaningful way some households are better positioned to access labour market opportunities than others.

Such an interpretation would fit quite readily into the theoretical framework outlined in this paper, in which search costs matter. If some households have better information or are better able to signal their quality to an employer, then the cost of making a successful match is reduced. This would lead to much higher probabilities of finding work. If the network and information story is correct, then the policy implication is more tricky. It becomes important to think about institutions which can reduce the search and matching costs in the labour market. Such institutions would probably have to work on both ends of the equation: providing information about opportunities to prospective workers and providing credible "references" to employers.

Alternative explanations are also possible. It may be, for example, that there are truly endogenous effects - that there are "dysfunctional" households which breed bad attitudes to work and which perpetuate bad outcomes over time. Such explanations (in the "culture of poverty" vein) are possible, but they would need to explain why these household effects seem to be much weaker in the urban areas. Somehow the urban context is more effective in dispersing such negative externalities. However if these explanations turn out to have more than a grain of truth in them, then the policy dilemma becomes truly intractable, since there seem few policy levers available to break open the processes within the household.

A Derivations

Let

$$y_{ij} = x_{ij}^{'}\beta + u_i + \varepsilon_{ij}$$

with $E(u_i) = 0$, $var(u_i) = \sigma_u^2$, $E\left(x_{ij}^{/}u_i\right) = 0$ and $E(\varepsilon_{ij}|u_i) = 0$. Since y_{ij} is a 0/1 variable, we have

$$\begin{aligned} E(y_{ij}|x_{ij}, u_i) &= x_{ij}^{'}\beta + u_i = p_{ij} &(6)\\ E(y_{ij}|x_{ij}) &= x_{ij}^{'}\beta = p_{ij}^{*} &(7)\end{aligned}$$

Note that p_{ij} is the probability that we would assign to individual i of being employed, knowing *both* her observable characteristics *and* which group (household) she comes from, while p_{ij}^{*} is the probability we would assign to her knowing only her observable characteristics.

Now

$$\varepsilon_{ij} = \begin{cases} 1 - p_{ij} & \text{with probability} \quad p_{ij} \\ -p_{ij} & \text{with probability} \quad 1 - p_{ij} \end{cases}$$

Hence

$$var(\varepsilon_{ij}|u_i, x_{ij}) = (1 - p_{ij})\, p_{ij} \tag{8}$$

Furthermore

$$\begin{aligned} E\left(\varepsilon_{ij}^2|x_{ij}\right) &= E\left(E\left(\varepsilon_{ij}^2|u_i, x_{ij}\right)|x_{ij}\right)\\ \sigma_{ij}^2 &= p_{ij}^{*}\left(1 - p_{ij}^{*}\right) - \sigma_u^2 \end{aligned}$$

i.e.

$$\sigma_u^2 + \sigma_{ij}^2 = p_{ij}^{*}\left(1 - p_{ij}^{*}\right) \tag{9}$$

Of course we could have derived this expression directly from (7).

A.1 Fixed effects

We can estimate p_{ij} by fixed effects estimation techniques, essentially doing OLS on

$$y_{ij} - \overline{y} = (x_{ij} - \overline{x}_i)' \beta + \varepsilon_{ij} - \overline{\varepsilon}_i \tag{10}$$

This will provide consistent estimates of β, although the error terms will be heteroscedastic and autocorrelated. The error variance is given by

$$\begin{aligned} var\left(\varepsilon_{ij} - \overline{\varepsilon}_i\right) &= \left(1 - p_{ij}\right) p_{ij} - \frac{2}{n_i}\left(1 - p_{ij}\right) p_{ij} + \frac{1}{n_i^2} \sum_{k=1}^{n_i} \left(1 - p_{ik}\right) p_{ik} \\ &= \left(\frac{n_i - 1}{n_i}\right)^2 \left(1 - p_{ij}\right) p_{ij} + \frac{1}{n_i^2} \sum_{k=1, k \neq j}^{n_i} \left(1 - p_{ik}\right) p_{ik} \end{aligned}$$

since by assumption the idiosyncratic errors are independent. The error covariance is

$$cov\left(\varepsilon_{ij} - \overline{\varepsilon}_i, \varepsilon_{ik} - \overline{\varepsilon}_i\right) = -\frac{1}{n}\left(1 - p_{ij}\right) p_{ij} - \frac{1}{n}\left(1 - p_{ik}\right) p_{ik} + \frac{1}{n_i^2} \sum_{l=1}^{n_i} \left(1 - p_{il}\right) p_{il}$$

From the OLS estimates of equation 10 we can also obtain an estimate of the common effect u_i. In particular

$$\widehat{u}_i = \overline{y}_i - \overline{x}_i' b$$

We can therefore get unbiased estimates of p_{ij} and p_{ij}^* as

$$\widehat{p}_{ij} = x_{ij}' b + \widehat{u}_i \tag{11}$$

$$\widehat{p^*}_{ij} = x_{ij}' b \tag{12}$$

A.2 Random effects

We can obtain an estimate of σ_u^2 from equations 8 and 9, i.e.

$$\widehat{\sigma}_{u,ij}^2 = \widehat{p^*}_{ij}\left(1 - \widehat{p^*}_{ij}\right) - \widehat{p}_{ij}\left(1 - \widehat{p}_{ij}\right) \tag{13}$$

This estimator will be biased, although consistent. We can improve on it by averaging within group i, i.e.

$$\widehat{\sigma}_{u,i}^2 = \frac{1}{n_i} \sum_{j=1}^{n_i} \widehat{\sigma}_{u,ij}^2 \tag{14}$$

In this case we can show that

$$E\left(\widehat{\sigma}_{u,i}^2\right) = -\overline{x}_i' V_b \overline{x}_i + \sigma_u^2 + \frac{1}{n_i^2}\sum_{j=1}^{n_i} \sigma_{ij}^2$$

where V_b is the true covariance matrix of the slope estimators b and n_i is the number of individuals in group i. We can improve on this yet further by taking an average of $\widehat{\sigma}_{u,i}^2$ across groups i. The simplest procedure is to take a weighted average (with weights proportional to group size), so that

$$\widehat{\sigma}_u^2 = \frac{1}{N}\sum_{i=1}^{h}\sum_{j=1}^{n_i}\left\{\widehat{p^*}_{ij}\left(1-\widehat{p^*}_{ij}\right) - \widehat{p}_{ij}\left(1-\widehat{p}_{ij}\right)\right\} \tag{15}$$

where N is the total sample size and h is the number of groups, with bias

$$\sum_{i=1}^{h}\frac{n_i}{N}\overline{x}_i' V_b \overline{x}_i - \frac{1}{N}\sum_{i=1}^{h}\overline{\sigma}_i^2$$

where $\overline{\sigma}_i^2$ is the average variance of the individual effect in group i.

The error covariance matrix (i.e. the covariance matrix of $u_i + \varepsilon_{ij}$) is by assumption

$$\begin{bmatrix} {}_1 & & 0 \\ & \ddots & \\ 0 & & {}_h \end{bmatrix}$$

with

$$_i = \begin{bmatrix} \sigma_{i1}^2 + \sigma_u^2 & \sigma_u^2 & \cdots & \sigma_u^2 \\ \sigma_u^2 & \sigma_{i2}^2 + \sigma_u^2 & \cdots & \sigma_u^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_u^2 & \sigma_u^2 & \cdots & \sigma_{ik}^2 + \sigma_u^2 \end{bmatrix}$$

We can transform the variables to take out the heteroscedasticity and autocorrelation with the transformation

$$Py = Px\beta + P\left(u + \varepsilon\right)$$

where

$$P_i = \begin{bmatrix} \frac{1-w_{i1}}{\sigma_{i1}} & \frac{-w_{i2}}{\sigma_{i1}} & \cdots & \frac{-w_{ik}}{\sigma_{i1}} \\ \frac{-w_{i1}}{\sigma_{i2}} & \frac{1-w_{i2}}{\sigma_{i2}} & \cdots & \frac{-w_{ik}}{\sigma_{i2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{-w_{i1}}{\sigma_{ik}} & \frac{-w_{i2}}{\sigma_{ik}} & \cdots & \frac{1-w_{ik}}{\sigma_{ik}} \end{bmatrix}$$

and $w_{ij} = \frac{1}{\sigma_{ij}^2 s_i}\left(1 - \frac{1}{\sqrt{s_i\sigma_u^2+1}}\right)$, with $s_i = \sum_{j=1}^{n_i} \frac{1}{\sigma_{ij}^2}$. Essentially we form the generalised differences

$$y_{ij}^* = y_{ij} - \sum_{j=1}^{n_i} w_{ij} y_{ij},\; x_{ij}^* = x_{ij} - \sum_{j=1}^{n_i} w_{ij} x_{ij}$$

in order to get rid of the autocorrelation induced by the u_i term and then divide through by σ_{ij} to remove the heteroscedasticity. We then regress y_{ij}^* on x_{ij}^*.

To implement this as FGLS we would use the estimate of σ_u^2 obtained in equation 15, as well as the estimate of σ_{ij}^2 obtained by substituting (11) into equation 8.

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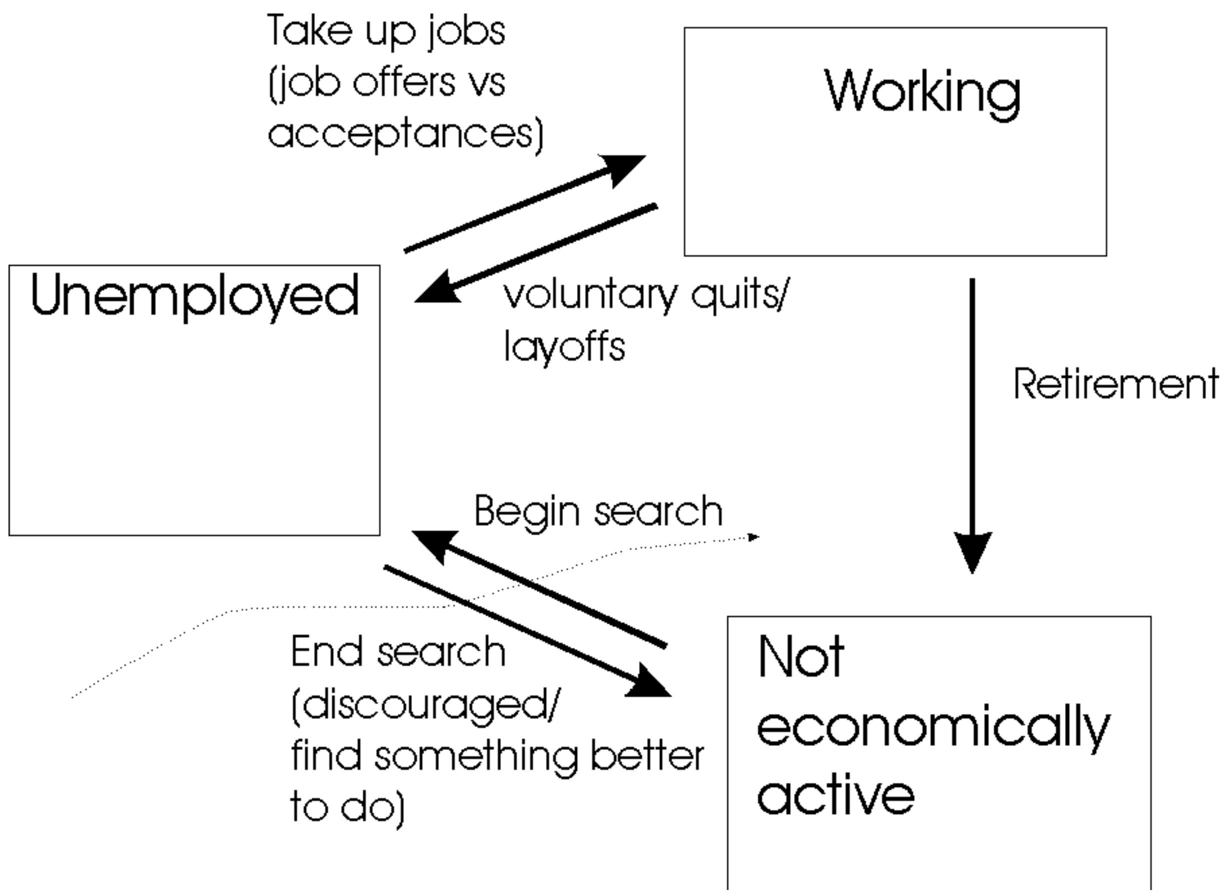

Figure 1: Some key labour market flows

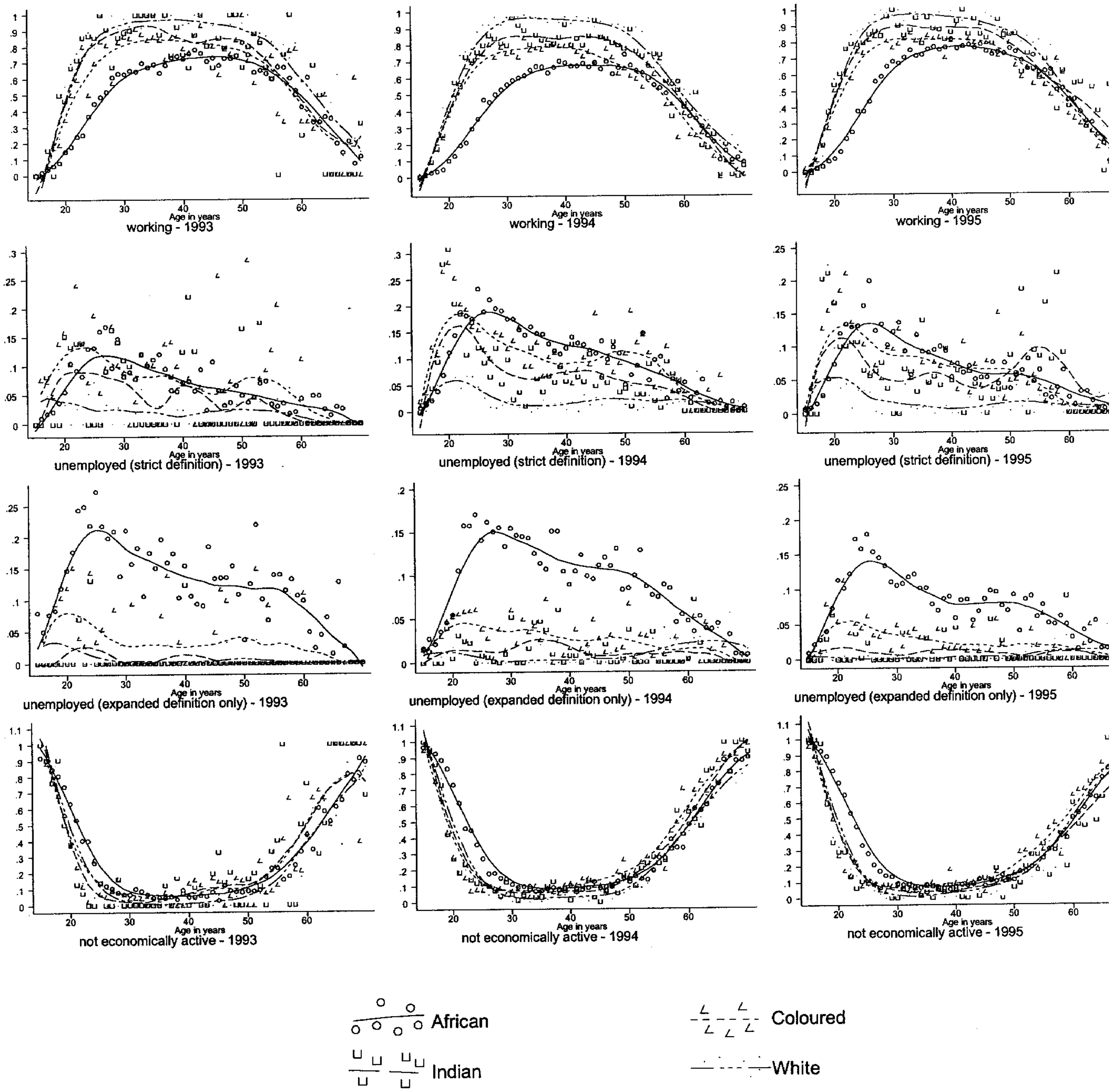

Figure 2: Stocks of individuals in different labour market states at different ages. The slope of the graph is an indication of the relevant flow rate, if the labour market is close to equilibrium.

Figure 3: The proportion of the unemployed engaged in active search (as measured by the household surveys) is remarkably steady at different ages.

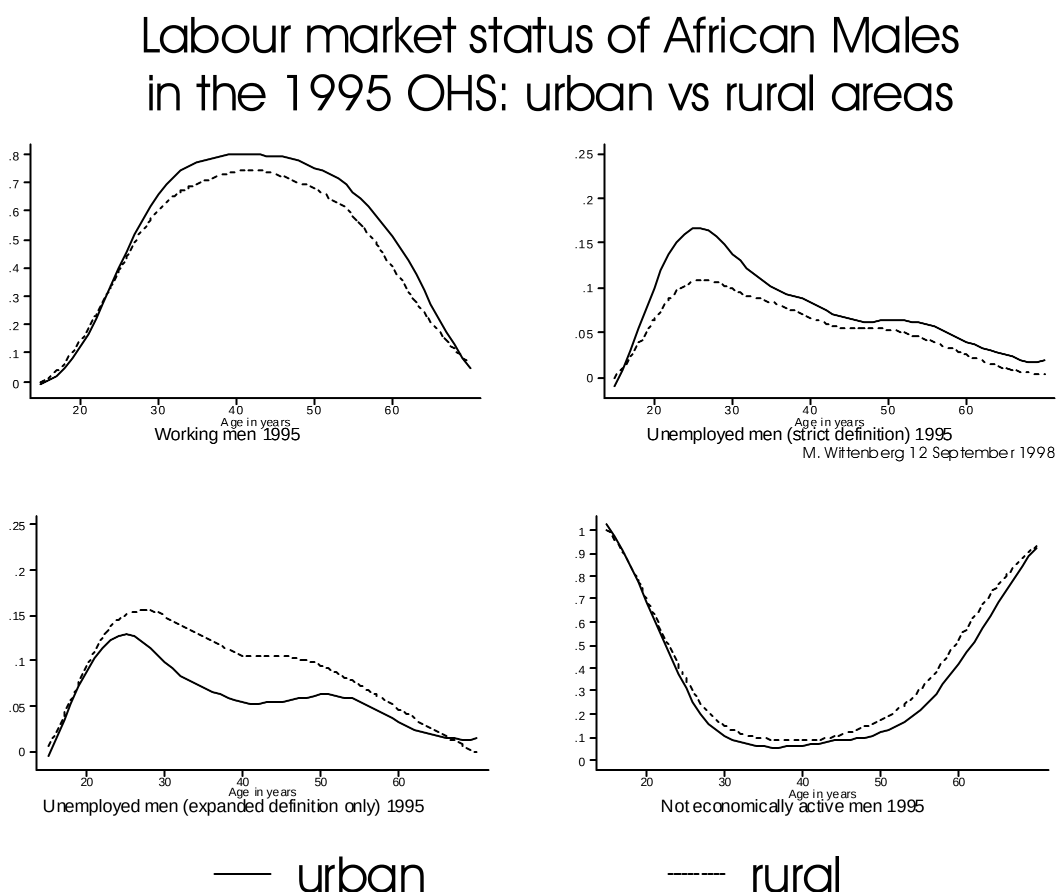

Figure 4: The pattern of labour market transitions seems to be different in urban and rural areas.

Table 1: Estimated distribution of working adults across households (1995 OHS)

Number of workers	Number of adults in the household: 1	2	3	4	5	6	7	8	9	10	11	12	13	14	Proportion of all workers	Proportion of all adults	Ratio
0	524,146	574,617	373,069	247,319	144,685	64,609	28,057	9,198	3,981	1,048	529	305			0	0.2185	0
1	980,728	1,458,506	631,618	394,131	220,774	101,271	39,567	15,072	8,024	2,545	777		194		0.3887	0.4014	0.97
2		1,104,197	448,083	322,526	162,895	94,183	35,775	17,692	7,411	2,438		192	513		0.4430	0.2811	1.58
3			103,413	99,725	71,578	35,165	17,671	7,062	2,826	5,476	179			173	0.1039	0.0646	1.61
4				44,276	25,418	18,224	8,365	5,792	1,925	2,105		190	292		0.0430	0.0236	1.82
5					13,978	4,832	2,916	952	2,184	933				305	0.0132	0.0067	1.96
6						1,990	596	4,249	1,738						0.0052	0.0028	1.89
7							475	485	379	215					0.0011	0.0005	2.05
8								1,742		410		276			0.0020	0.0009	2.19
Proportion w	0.6517	0.5844	0.3937	0.3419	0.2918	0.2623	0.2346	0.2860	0.2460	0.2750	0.0804	0.2902	0.1839	0.3055			

Table 2: Summary statistics of sample variables

	Men: N	Mean	S.D.	Min	Max	Women: N	Mean	S.D.	Min	Max
workers	25314	0.428	0.495	0	1	30517	0.242	0.428	0	1
highed	25314	7.542	3.890	0	15	30517	7.369	4.022	0	15
age	25314	32.172	13.484	15	65	30517	33.039	13.866	15	65
age2	25314	1216.8	1005.3	225	4225	30517	1283.8	1053.8	225	4225
spills	25314	0.498	0.812	0	8	30517	0.639	0.771	0	8
Household composition:										
Male infant	25314	0.052	0.095	0	0.6	30517	0.068	0.107	0	0.75
Fem. Infant	25314	0.052	0.095	0	0.667	30517	0.067	0.107	0	0.8
Male child	25314	0.071	0.108	0	0.667	30517	0.083	0.117	0	0.75
Fem. child	25314	0.074	0.111	0	0.667	30517	0.086	0.118	0	0.8
Male youth	25314	0.232	0.215	0	1	30517	0.128	0.148	0	0.833
Fem. Youth	25314	0.140	0.143	0	0.8	30517	0.226	0.174	0	1
Male adult	25314	0.176	0.220	0	1	30517	0.097	0.119	0	0.8
Male old	25314	0.026	0.080	0	1	30517	0.025	0.068	0	0.667
Fem. Old	25314	0.030	0.075	0	0.667	30517	0.038	0.092	0	1
Avg educatio	25314	7.432	3.017	0	15	30517	7.467	3.000	0	15
Nr of adults	25314	3.991	1.985	1	14	30517	3.953	1.914	1	14

Table 4: Household effects on the probability of finding work - urban areas (1995 OHS)

	L.P.M.				Logit			
	(1) Simple		(2) Fixed effects		(3) Fixed effects (clogit)		(4) Random effects	
	Women	Men	Women	Men	Women	Men	Women	Men
gender		-0.2260		-0.1457		0.7391		-0.0538
		(0.0947)		(0.0458)		(0.5245)		(0.531)
highed	0.0180	0.0074	0.0203	0.0081	0.1546	0.0953	0.1263	0.0974
	(0.0024)	(0.0034)	(0.0015)	(0.0019)	(0.0127)	(0.0143)	(0.0125)	(0.0184)
age	0.0739	0.0910	0.0661	0.0882	0.5924	0.6262	0.6062	0.6373
	(0.0025)	(0.0036)	(0.0018)	(0.0026)	(0.0204)	(0.026)	(0.0172)	(0.0236)
age2	-0.0008	-0.0010	-0.0007	-0.0010	-0.0065	-0.0069	-0.0068	-0.0071
	(0)	(0)	(0)	(0)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
spillovers	-0.0017	0.0138						
	(0.0078)	(0.0121)						
Household composition:								
Male infant	-0.2846	0.3676					-0.8288	2.3871
	(0.0531)	(0.0823)					(0.2728)	(0.4419)
Fem. Infant	-0.2222	0.4053					-0.4725	2.3673
	(0.0533)	(0.0843)					(0.2695)	(0.442)
Male child	-0.1182	0.2681					-0.3272	1.3400
	(0.05)	(0.0804)					(0.2593)	(0.4216)
Fem. Child	-0.0434	0.0986					-0.0740	0.1494
	(0.05)	(0.0774)					(0.2504)	(0.4013)
Male youth	-0.0626	0.3045					0.6142	1.9231
	(0.0481)	(0.0683)					(0.2203)	(0.312)
Fem. Youth	0.0394	0.3823					1.3793	2.0487
	(0.0408)	(0.0588)					(0.1963)	(0.3107)
Male adult	-0.3148	0.2274					-1.2697	1.0046
	(0.0514)	(0.0833)					(0.2501)	(0.3355)
Male old	-0.5328	0.0666					-2.2859	0.7612
	(0.0817)	(0.1333)					(0.4567)	(0.6026)
Fem. Old	-0.2025	-0.6473					-1.4389	-4.8978
	(0.0646)	(0.1026)					(0.3447)	(0.5381)
Avg education	0.0143	0.0074					0.0726	0.0081
	(0.003)	(0.0042)					(0.0161)	(0.0237)
Nr of adults	-0.0212	-0.0529					-0.2349	
	(0.0034)	(0.0054)					(0.0127)	
Intercept	-1.1636		-1.1500				-13.6522	
	(0.0546)		(0.0323)				(0.3906)	
N	22078		22078		14812		22078	
rho			0.3779				0.1360	
corr(u,X)			0.0069					

Table 5: Household effects on the probability of finding work - nonurban areas (1995 OHS)

	L.P.M.				Logit			
	(1) Simple		(2) Fixed effects		(3) Fixed effects (clogit)		(4) Random effects	
	Women	Men	Women	Men	Women	Men	Women	Men
gender		-0.6623		-0.4626		0.5092		-2.3853
		(0.0571)		(0.032)		(0.443)		(0.4647)
highed	0.0088	-0.0010	0.0114	0.0014	0.1373	0.0289	0.1057	0.0542
	(0.0013)	(0.002)	(0.001)	(0.0012)	(0.0108)	(0.0119)	(0.0107)	(0.0159)
age	0.0478	0.0897	0.0401	0.0811	0.5701	0.6553	0.5407	0.7050
	(0.0014)	(0.002)	(0.0012)	(0.0018)	(0.0191)	(0.0234)	(0.0154)	(0.0204)
age2	-0.0005	-0.0010	-0.0004	-0.0009	-0.0065	-0.0073	-0.0063	-0.0071
	(0)	(0)	(0)	(0)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
spillovers	0.0489	0.0525						
	(0.0058)	(0.008)						
Household composition:								
Male infant	-0.2604	0.1772					-1.3464	2.3871
	(0.04)	(0.0607)					(0.2671)	(0.396)
Fem. Infant	-0.2117	0.2613					-1.0359	1.3089
	(0.0427)	(0.0632)					(0.2676)	(0.3988)
Male child	-0.2438	0.1038					-1.4312	0.1650
	(0.0412)	(0.0586)					(0.2562)	(0.3817)
Fem. Child	-0.2856	0.0848					-1.8835	-0.0088
	(0.0408)	(0.0599)					(0.2583)	(0.3821)
Male youth	-0.0447	0.4077					1.3091	3.1215
	(0.0411)	(0.0563)					(0.2396)	(0.3298)
Fem. Youth	0.0657	0.4361					2.0723	2.8549
	(0.035)	(0.0503)					(0.219)	(0.3222)
Male adult	-0.2706	0.1522					-0.6695	0.7665
	(0.0483)	(0.0639)					(0.2864)	(0.376)
Male old	-0.4591	-0.1779					-3.1533	-0.9739
	(0.0561)	(0.0871)					(0.463)	(0.5854)
Fem. Old	-0.2959	-0.8315					-2.6559	-7.4362
	(0.0404)	(0.0716)					(0.3863)	(0.5444)
Avg education	-0.0042	-0.0037					-0.0791	-0.1016
	(0.0018)	(0.0025)					(0.014)	(0.0202)
Nr of adults	-0.0314	-0.0631					-0.3793	
	(0.0024)	(0.0032)					(0.014)	
Intercept	-0.4887		-0.6289				-10.6647	
	(0.0379)		(0.0223)				(0.3487)	
N	33753		33753		18609		33753	
rho			0.4490				0.3363	
corr(u,X)			0.0359					

Table 3: Household effects on the probability of finding work (1995 OHS)

	L.P.M.				Logit			
	(1)		(2)		(3)		(4)	
	Simple		Fixed effects		Fixed effects (clogit)		Random effects	
	Women	Men	Women	Men	Women	Men	Women	Men
urban	0.0452						0.4773	-0.0567
	(0.0066)						(0.0408)	(0.0552)
gender		-0.4537		-0.3037		1.0737		-1.1188
		(0.0534)		(0.0263)		(0.3322)		(0.3436)
highed	0.0147	0.0034	0.0174	0.0035	0.1595	0.0468	0.1207	0.0715
	(0.0012)	(0.0012)	(0.0008)	(0.001)	(0.0081)	(0.0087)	(0.008)	(0.0119)
age	0.0597	0.0903	0.0504	0.0834	0.5825	0.6342	0.5669	0.6741
	(0.0014)	(0.0014)	(0.001)	(0.0015)	(0.0139)	(0.0172)	(0.0114)	(0.0153)
age2	-0.0007	-0.0010	-0.0005	-0.0009	-0.0065	-0.0070	-0.0065	-0.0076
	(0)	(0)	(0)	(0)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
spillovers	0.0256	0.0286						
	(0.0048)	(0.0048)						
Household composition:								
Male infant	-0.2818	0.2600					-1.0715	1.3220
	(0.0316)	(0.0316)					(0.1903)	(0.2908)
Fem. Infant	-0.2183	0.3293					-0.6841	1.7479
	(0.0331)	(0.0331)					(0.1898)	(0.2931)
Male child	-0.2065	0.1786					-0.9576	0.5830
	(0.0314)	(0.0314)					(0.1813)	(0.2792)
Fem. Child	-0.1975	0.0906					-1.0585	0.0040
	(0.0313)	(0.0313)					(0.1793)	(0.2744)
Male youth	-0.0504	0.3516					1.0450	2.5014
	(0.0312)	(0.0312)					(0.1632)	(0.2273)
Fem. Youth	0.0386	0.4142					1.7282	2.4654
	(0.0264)	(0.0264)					(0.1475)	(0.2237)
Male adult	-0.2719	0.1774					-0.8468	0.7717
	(0.0358)	(0.0358)					(0.19)	(0.2525)
Male old	-0.4980	-0.0792					-2.8156	-0.3154
	(0.0466)	(0.0466)					(0.3269)	(0.4195)
Fem. Old	-0.2725	-0.7687					-2.0805	-6.4113
	(0.0354)	(0.0354)					(0.2595)	(0.3832)
Avg education	0.0022	-0.0015					-0.0290	-0.0588
	(0.0016)	(0.0016)					(0.0104)	(0.0152)
Nr of adults	-0.0284	-0.0585					-0.3224	
	(0.002)	(0.002)					(0.0096)	
Intercept	-0.7909		-0.8515				-11.9587	
	(0.033)		(0.0185)				(0.2565)	
N	55831		55831		33421		55831	
rho			0.4193				0.2566	
corr(u,X)			0.0268					