Social Networks and Wages in South Africa

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Abstract

Although it is a stylized fact that social networks play an important role in job search, their impact on labour market outcomes, namely wages, is still disputed. Using data from South Africa, this paper investigates the effect of job search method and, in particular, the role of social distance (the use of relatives versus friends) on wages of African, Coloured and White youth. We show that the use of social networks is generally associated with large wage penalties, that can be large. In particular, the use of relatives results in significant penalties for Africans, the race group among who unemployment is higher. This suggests that firms may discount the value of the information provided by referees if they are close to job seekers.

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1 Introduction

An extensive literature in economics and other social sciences, recently reviewed in Marsden and Gorman (2001), Ioannides and Loury (2004) and Topa (2011), analyzes the importance of social networks for the functioning of labour markets. ¹ One of the stylized facts that emerges from this work is that their use is pervasive and generally productive. As a result, a large fraction of jobs are found through social networks. ²

A natural consequence of this empirical regularity is to ask whether the use of social networks affects outcomes in the labour market, in particular wages and tenure, and if they do, for whom. As Mouw (2003, p. 868) notes, “This is no trivial issue. If using contacts seems to have little overall impact on labour market outcomes, then perhaps economic models of the labour market can safely ignore ‘embeddedness’ … without sacrificing explanatory power.”

The growing number of studies, both theoretical and empirical, that address this question can be organized around two competing hypotheses. The “good matches” hypothesis, which dates back to seminal study by Rees (1966) and, more formally, Montgomery (1991), Saloner (1985) and Simon

¹The use of social networks refers to job seekers communicating with friends, relatives and acquaintances about employment opportunities and firms using informal referrals and recommendations to find workers.

²This is true in both developed and developing countries. See, for example, Bewley (1999) who finds that, in the USA, 30-60% of the jobs are found through social contacts. See also Granovetter (1974) and Holzer (1987) for the USA and Bentolila and Suarez (2010) for a recent analysis of the role of social networks in several countries of the European Union. In developing countries see Magruder (2010) and Burns, Godlonton, and Keswell (2010) for evidence in South Africa, Calvo-Armengol and Zenou (2005) for an analysis of the role of social networks in the functioning of the labour market in Egypt, and Lawler et al. (1995) for a comparison of human resource management practices of firms in India and in Thailand and the extent of use of internal referrals to fill different jobs.
and Warner (1992), interprets social networks as screening or monitoring mechanisms that increase the quality of the match between worker and firm by reducing informational asymmetries, leading to higher productivity which would be reflected in a higher wage. The “limited choices” hypothesis, initially suggested by Loury (2006), interprets social networks as mechanisms that allocate workers to jobs at a relatively low cost for both firms and prospective workers. Because search through networks is limited by its characteristics, including the job information that its members have access to, it may lead to sub-optimal matches and associated wage penalties.

We briefly review both these different interpretations in section 2, emphasizing that they share one important similarity: the importance of the referee, both in terms of motivation and identity, is usually unexamined, replaced with the assumption that “present workers tend to refer people like themselves ...” (Rees, 1966, p. 562). Although the importance of homophily, that “birds of a feather flock together”, has long been recognized in the social network literature (see McPherson, Smith-Lovin, and Cook, 2001, for a review), these two competing hypotheses emphasize different aspects of similarity between members of a network: productive ability in the first case, identity in the second.

In section 2 we also discuss some of the recent work that addresses the possible conflict between these two dimensions of the referee’s decision and raise the possibility of referee opportunism, that is, that referees may indicate someone who is not of high ability but who is socially close. An intuitive consequence of this possibility, that we explore in this paper, is that firms may react by applying a wage penalty that is a positive function of how
close the referee is to the worker, a prediction that is close, in spirit, to the
important study of Granovetter (1974) which emphasizes the positive im-
 pact of increased social distance (weak ties) between referee and job seeker
on the probability of finding a job.

We empirically estimate the effects on wages of finding a job through
the use of different social contacts using data from the Cape Area Panel
Study (CAPS), which we present, succinctly, in section 3. The CAPS is
a particularly valuable data for this purpose, for two reasons. The first
is the wealth of information on respondents’ employment outcomes, job
search methods, and personal characteristics such as education and working
experience, for a large sample of youth across several years (2002-2006).
The second is the importance of the functioning of the labour market in
addressing issues of poverty and inequality in the South African context, a
point that we also discuss, briefly, in section 3.

In section 4 we present our results. We find that, controlling for individ-
ual and job characteristics, including unobserved heterogeneity, finding a job
through social networks carries a wage penalty for all race groups suggesting
that the “good matches” hypothesis finds no support in this context. This
negative effect is compounded by social proximity, especially in the case of
African youth, with higher penalties associated with the use of contacts who
are socially closer (relatives and household members).  

A note on terminology. We adopt the labels used in CAPS and by Seekings and
Nattrass (2005, p. ix) and use the word ‘African’ to refer to peoples classified under
apartheid as “native”, “bantu” or “black”, the word ‘White’ to refer to people classified
as European or white, and the word ‘Coloured’ to refer to the people that don’t fit the first
two categories, including descendants of the indigenous Khoi and San, the descendants of
“Malay” slaves from Indonesia and those with mixed race ancestry.
We conclude in section 5. An understanding of the significance of social networks to individual job search outcomes may have important policy implications in the high unemployment context of South Africa. If youth are using social networks to acquire jobs even though they are associated with large wage penalties, this may be a sign that labour market institutions do not facilitate formal job search for these individuals to find more suitable employment.

2 Wages and social networks: a brief review of the literature

Most of the economic studies of the role of social networks in the functioning of labour markets build on the job matching approach and its assumption that not all matches between workers and firms are optimal. Prospective workers are heterogeneous in preferences for different types of jobs and in their productivity in those jobs, while jobs are heterogeneous in the skills required and in their non pecuniary characteristics (Johnson, 1978, Jovanovic, 1979, Viscusi, 1980). Uncertainty and imperfect information about any of these aspects may lead some hired workers to be poor matches for the jobs they hold, either because the job seeker misjudges the job or the firm misjudges the prospective worker. The use of social networks in job search is then seen as an effective method for firms and potential workers to improve the matching process (Montgomery, 1991, Saloner, 1985, Simon and Warner, 1992), at relatively low costs (Holzer, 1987). The label “better matches” derives from this interpretation.
If the use of job contacts makes it more likely that job seekers and firms will obtain accurate information about each other, then this should impact positively on wages and tenure. For example, in the model proposed by Jovanovic (1979) wages are positively related to tenure. If a job match turns out to be poor, it is more likely that job separation will occur earlier rather than later (that is, as soon as the low quality of the match becomes apparent to the worker and the firm) while longer tenure is a sign that the worker is suitable for the job. Similarly, if wages are set equal to worker’s marginal product, they should be higher on average for those workers that are proven to be productive and consequently have longer tenure. Simon and Warner (1992) extend this reasoning to suggest that wages may be higher from the start of employment for a worker that is referred to the firm as the firm anticipates higher than average productivity.

Implicit in this analysis since, at least, Rees’ work, is the assumption that workers refer others like themselves and that, because of this, “worker referrals . . . usually provide good screening for firms who are satisfied with their present workforce” (Rees, 1966, p.562). This assumption is explicitly made in Montgomery (1991), where the motivations of the referee are replaced with the assumption that abilities are correlated across individual members of a network. However, the benefits of a network are conditional on its characteristics and there is abundant evidence that homophily in networks is not limited to one specific characteristic (in this case, ability), rather it spans several characteristics (such as gender, race, age) which are not inherently productive.

The “limited choices” hypothesis emphasizes that there may be costs
associated with the use of social networks precisely because productivity irrelevant characteristics play a role in network formation and, as such, in access to the information it may transmit. While networks may be used because of convenience and low monetary costs relative to formal methods, they provide the job seeker with a range of job opportunities limited by the characteristics of their social network, that may not be suited to the characteristics of the job seeker, unlike the wider range of jobs that are potentially available through formal methods (Bentolila and Suarez, 2010). As a result, wages in jobs found through social networks will be equal to or lower than in jobs found through formal methods. The clearly contrasting wage implications of the limited choices and good matches hypotheses can be used to empirically test between these two hypotheses. 4

Several recent studies have provided support to the “limited choices” hypothesis. Combining personnel files and job-histories of workers at a manufacturing firm, Antoninis (2006) found that new recruits receive a higher starting wage when recommended to the job by an individual with direct experience of their productivity but that the use of referrals from friends

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4It is important to note, as Loury (2006) does, that whilst longer job tenure should be the result of good matches it may also be consistent with the limited choices hypothesis and so can not be a definitive test between the theories. Simon and Warner (1992) argue that jobs obtained through contacts with more information (i.e., recruiters or acquaintances inside the firm) lasted significantly longer than jobs obtained through want ads or private agencies and that this is evidence of the benefits of using networks. In contrast however, Topel and Ward (1992) argue that the average young worker holds seven jobs in the first 10 years of his working life and that job mobility accounts for one-third of wage growth during this period. If workers chose to change jobs voluntarily this must be because of having better alternative jobs available and so such job mobility should increases wage. In contrast, young workers that stick with jobs for longer than average periods of time may miss out on opportunities to obtain higher wages. Keith and McWilliams (1995) and Abbott and Beach (1994) show that the effects of job mobility on wages depend on whether the job change was voluntary or involuntary. Both studies find that voluntary separation increases wages while involuntary separation does not.
and relatives has no effect on the starting wage and may even be negatively related to wages in unskilled jobs. Similarly, Bentolila and Suarez (2010) found that contacts are associated with wage discounts of at least 2.5%, although they also reduce unemployment duration by 1-3 months on average, while Pellizzari (2010), using data from the European Community Household Panel, finds that penalties and premiums are equally common across the countries, a result that he attributes to the mediating effect of the labour market institutions of each country.  

Of particular interest in this paper is the idea, suggested by Loury (2006) and Calvo-Arnegnol and Jackson (2007), that heterogeneity in the characteristics of social networks may result in the possibility of the limited choices hypothesis finding support for some job seekers but not for others, that is, that different population groups may experience different network effects according to the differences in the characteristics of their networks. An extensive literature provides empirical support to this possibility.

Korenman and Turner (1996) reported that, among young workers in inner-city Boston, Whites who found jobs through contacts received much larger wage gains (19% higher) than Blacks with similar observable characteristics. Smith (2000) showed that gender wage differences were small for those using formal job-search methods. In contrast, she found larger wage differences between Hispanics and Whites who used personal contacts to find jobs compared to those who used more formal means.

Using data on contacts amongst a group of Dartmouth college seniors,  

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5 Finally, several other studies have found no wage effect associated the use of informal search methods (Bridges and Villemez, 1986, Holzer, 1987, Mouw, 2003).
Marmaros and Sacerdote (2002) found that the students networking with fraternity/sorority alumni were more likely to get better paying and more prestigious jobs. However, there were significant gender and race differences and the type of contacts used had an impact on the quality of employment found. For example, women were less likely to get fraternity/sorority help, more likely to use help from professors and equally likely to get help from relatives. Loury (2006) also finds heterogeneity in network effects according to the gender of the contact, with prior generation male relatives having a positive and larger effect than female friends and relatives.

It is also important to consider that networks are not formed with the sole purpose of disseminating information important for the functioning of the labour market, rather they may provide a variety of functions (including, and importantly in developing countries, insurance). It seems likely that there will exist spillovers from one context/purpose to another. This possibility was also raised by Rees (1966), who notes that “the few firms who deliberately avoid informal sources are either those who are seeking to upgrade their work force or those who have had bad experience with nepotism or cliques” (p. 562, emphasis added). Similarly, Antoninis (2006, p.135) remarks, in criticizing Montgomery (1991) assumption of correlated abilities between referees and job seekers, that “...one observes that individuals take active steps to ensure employment for members of their family network for reasons that are often unrelated to whether their relative has a similar level of ability. Firms often respond to such recommendations favorably despite their knowledge that they may have little to do with the new recruits’ productivity potential”.

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Some recent work (Magruder and Beaman, 2012, Fafchamps and Moradi, 2011, Bandiera, Barankay, and Rasul, 2010) analyzes the possible implications of this overlap for productivity in a variety of contexts, concluding that referee opportunism may lead to lower productivity. The results of Magruder and Beaman (2012) are particularly interesting in this context. The authors asked workers to refer people for a task. Referees were randomly allocated to two groups: they would either receive a fixed amount per referral or an amount that depended on the performance of the referred person. When referral is made contingent on worker’s productivity, participants are less likely to refer a relative and more likely to refer someone with high productivity. Additionally, the effect of the incentive depends on the quality of the referee: participants of low ability do not seem capable of recruiting high ability workers. This work then provides mixed support to the “good matches” hypothesis: although referee and worker’s ability may be correlated (as assumed by Montgomery (1991)), they do not need to be in the absence of the right incentive, in which case referee’s are motivated by the exchange of favors with friends and relatives.

The consequences of such opportunistic behavior are intuitively simple: firms may withdraw from reliance on social networks as a recruitment mechanism (as mentioned in Rees (1966)) or may take into account such productivity-irrelevant motivations when making a (lower) wage offer. Because the motivation to refer someone who is not necessarily a good match should increase the closer referee and worker are, so such the wage penalty. In section 4 we present estimates of the effect of social networks which support this interpretation, particularly among the group who experience higher
unemployment rates (African youth).

3 Context and Data: Social Networks and Wages in South Africa

In South Africa, unemployment has been persistently high, having increased in the decade following the end of apartheid and remaining high ever since (Kingdon and Knight, 2004, 2007) and, as in other countries, youth unemployment is higher than the overall rate. Race still plays an important role in describing unemployment. Morrow, Panday, and Richter (2005), using data from the Umsobomvu Youth Survey conducted in 2005, found a very high rate of youth unemployment for Africans (above 60%), compared to White and Coloured youths (less than 10%).

Burns, Godlonton, and Keswell (2010) argue that, in such a context of high unemployment, it may be rational to decide not to actively search for work through formal methods if the cost of such search is high and there are significant opportunities to find work through networks. The productivity of social networks in the context of the South African labour market has been studied by Burns, Godlonton, and Keswell (2010), who define social networks as language groups and find that its use increases employment probability between 3-12%, and by Magruder (2010), who focus on the role of employment status of father’s on the employment probabilities of sons, and finds that a 10% growth rate in the father’s industry led to an increase of

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6 At the end of 2010, Statistics South Africa reported unemployment for the last quarter of that year at 24% (defined as individuals aged 15-65 searching for work and not currently working).
3-4% in the employment probability of sons. His conclusion that fathers are critical network members for their sons has important implications for the persistence of inequality in South Africa which, as shown by Leibbrandt and Woolard (2001), is determined primarily by the functioning of the labour market. The higher productivity of social networks in terms of employment probability would then limit intergenerational mobility (Magruder, 2010), creating a cycle that is akin to the mechanism of inequality traps presented in Bourguignon, Ferreira, and Walton (2007). 7

However, the variation in employment probability is not the only way in which social networks may relate to inequality. Wage inequality among the employed may also matter if jobs found through networks vary systematically from jobs found through formal search or, more simply, if the use of contacts does not improve the quality of the match between firms and job seekers. Previous studies have not related wages and job search method to explore this possibility.

This paper uses data from the Cape Area Panel Study (CAPS), described in Lam, Seekings, and Sparks (2008), to address the question of whether the use of social networks has an impact on wages. 8 CAPS is a longitudinal study of a random sample of 4758 youth aged 14-22 in 2002

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7 Recent theoretical work suggests that the implications of the use of social networks in the labour market are in fact not trivial, and can range from differences in the aggregate unemployment rate (Kuzubas, 2009) to long run inequality between groups (Calvo-Armengol and Jackson, 2004, Arrow and Borzekowski, 2003).

8 The Cape Area Panel Study Waves 1-2-3 were collected between 2002 and 2005 by the University of Cape Town and the University of Michigan, with funding provided by the US National Institute for Child Health and Human Development and the Andrew W. Mellon Foundation. Wave 4 was collected in 2006 by the University of Cape Town, University of Michigan and Princeton University. Major funding for Wave 4 was provided by the National Institute on Aging through a grant to Princeton University, in addition to funding provided by NICHD through the University of Michigan.
living in the Cape Town Metropolitan Area. The study focuses on a wide range of important and related outcomes for youth during the transition to adulthood, including schooling and labour market participation. All youth were initially interviewed in 2002 (wave 1) and then in 2003-2004 (wave 2), 2005 (wave 3) and 2006 (wave 4).  

In this paper, we limit the analysis to the effect of social networks on the wages of respondents from 15 to 24 years of age who were employed full time. This age interval corresponds to the United Nations definition of “youth” (United Nations, 1996), a period best understood as one of transition from the dependence of childhood to the independence of adulthood. The emphasis on independence as a defining characteristic of adulthood motivates our emphasis on full time employment.

As discussed at greater length in World Bank (2006), the transition to adulthood is an economically important time for at least two reasons. Firstly, youth begin to reap the rewards of investment in human capital as they make critical decisions, in an uncertain environment, about when to leave education and enter the labour market. Part of that uncertainty derives from youth inexperience with employment and the search for employment: the low quality of a match with a job may only be discovered by experience. Secondly, early bad experiences in the transition to the labour

\[\text{9We do not use data from wave 1 in the analysis as the questions regarding the key variables of interest, job finding method, were not coded in the same way as in subsequent waves. After the first versions of this paper were written, one more wave (wave5, 2009) became available. However, job history of respondents was not collected in a way similar to previous waves. For these reasons, the analysis is limited to the period 2003-2006 (waves 2 to 4).}

\[\text{10The lower bound of this interval also matches the age at which schooling stops being compulsory while the upper bound matches the one in the definition of youth by the United Nations.}

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market, such as long periods of unemployment or jobs with low wages and low skills, are scarring experiences, disadvantaging those who suffer them in terms of their future labour market outcomes. For that reason, whether social networks act as mechanisms that facilitate good matches or rather simply allocate workers to jobs at low cost (and potentially limit the range of matches available to prospective workers) is potentially more important to youth than to older workers.

Table 1 presents information on both job and individual characteristics in our sample. The first observation is that Whites’ wages are about twice that of Africans and Coloureds. Such differences in wages between race groups may be due, at least in part, to systematic differences in education. The second observation is that while White youth have, on average, slightly more years of education than Africans and Coloureds, this difference is not very large, an unsurprising fact given what others have written about generally high enrolment rates in primary and high school across all race groups (Anderson, Case, and Lam, 1999). However, years of education tells us nothing about differences in educational quality. We can capture some of these differences in the results of the literacy and numeracy ability test conducted by CAPS. As shown, there are wide differences across races, with the mean literacy and numeracy score for Whites (close to 85%) being much higher than for Africans (barely above 50%).

Apart from differences in education, differences in family background

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11 Hourly pay in Rands was calculated from data on monthly pay and hours worked each month. The sample includes only those participants that provided data on both monthly pay and monthly hours worked.

12 The literacy and numeracy score measures the number of correct answers in a test consisting of 45 questions, conducted in the the first wave of CAPS.
may lead to differences in a range of personal characteristics (or in the quality of a network) that may be valued in the labour market. Again, we find large differences across races, with a higher proportion of Whites coming from a financially well-off background and living mostly in formal urban areas throughout their lives than Africans. Parents of White youth are also more educated (again measured in years of education) than parents of youth of other race groups, and the differences are much larger than in the current generation. The data on educational background of mothers and fathers allow us to address one other background difference: although the importance of missing values for father’s education is always higher than for mother’s education, this difference is relatively small in the case of Whites (354 observations on mother’s education versus 326 observations on father’s education) and relatively large in the other two race groups (2128 versus 1577 and 778 versus 511 in the case of Coloureds and Africans, respectively). If we are willing to speculate that such differences reflect less acquaintance with fathers than with mothers while growing up, then such differences are relatively minor in the case of White youth, but relatively important in the case of Coloured and Black youth, a result that seems particularly relevant in light of Magruder (2010) conclusion regarding the importance of fathers as job contacts for their sons.

A key advantage of CAPS for the purposes of this paper is the exis-

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13 “Family well-off during childhood” corresponds to an individual who responded either “very comfortable” or “comfortable” when asked to characterize their families financial situation as a child, while “Family poor during childhood” corresponds to those who responded either “very poor” or “poor” to that same question. “Lived mostly in formal urban areas” corresponds to those who reported having spent most of their life in formal urban areas, as opposed to rural or informal urban areas.
tence of a complete, month by month, labour market history constructed for the years 2003-2006 (waves 2 to 4) which also includes detailed information about job finding methods. This information is used in three ways. Firstly, it allows us to construct different measures of work experience, including accumulated experience in the same occupation and in the same industry, rather than simpler measures of overall experience in the labour market. Secondly, it allows us to construct a set of industry and occupation fixed effects which help to control for the possibility that firms in different industries may have different search strategies for different jobs. Finally, it allows us to quantify the importance of job search method on labour market outcomes.

Regarding this last use of the data, we consider three mutually exclusive possibilities: formal methods, assistance from a relative or assistance from a friend. These last two variables express the importance of social networks and differ in the assumed social proximity between the job seeker and the referee, as we assume that relatives are socially closer than friends. What Table 1 shows is that there are important differences in terms of how youth find a job: although it is clear that all race groups use social networks to find a large portion of their jobs, Whites successfully used formal methods in about 40% of the jobs while the corresponding number for Africans and Coloureds is slightly less than 1/3 and slightly above 1/4 of

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14 Observations of self-employment, working for the family business, missing observations and the category “other”, have been dropped. We also dropped those jobs where the respondent was in contact with the firm because of past employment with them.

15 Formal methods comprise responding to a newspaper advert, getting work through an employment agency, submitting CV’s directly to, or visiting firms. Relatives comprise either a household member or a relative outside the household.
the jobs, respectively. There are also differences regarding the relative importance of relatives versus friends: conditional on finding a job through social networks, Whites are slightly more reliant on friends (58% of them find jobs found through networks) than Coloureds and Africans (52% and 53%, respectively).

Before we present the analysis of the relation between search method and wage, it is important to qualify the importance of social networks. Table 2 shows that, of the 1132 individuals who had more than one job (representing more than 80% of our sample of individuals), 193 (or 17% of the sub-sample) found all jobs using formal methods. If we add to this number the 279 individuals (25% of the sub-sample) who found jobs using a mix of formal methods and social contacts (either friends, relatives or both), we see that over 40% of the individuals in the sample have some experience with formal search methods. As expected, given what is stated above, this percentage is slightly higher for Whites (64%) than Africans and Coloureds (43% and 39% respectively).

Table 3 further qualifies the importance of social networks. It presents the choice of job search method by respondents who are full time employed and actively searching for a different job. The most noticeable aspect is that in only 3% of these searches do respondents rely exclusively on social networks, and this is true irrespective of whether they had been successful in using this method in securing their current job. In contrast, the rule is to use both formal methods and social networks, a strategy adopted in almost 80% of the cases for which we have information. Clearly, there does not seem to exist any specialization in job search method (either the use of
formal methods or social networks) in this sample.  16

Tables 4 and 5 seem to suggest that such conclusion is not specific to
any occupation or industry. Table 4 also allows us to conclude about the
relative importance of social networks in finding jobs with different skill
levels.  17 There is some evidence that differences in required skills lead
to privileging hiring through social networks, but it points in an opposite
relation from what we would expect from the “good matches” hypothesis:
the importance of social networks increases as the skills level of the job
decreases (79% of the jobs in the lowest skill category are filled through
social networks, substantially more than in the highest skill category, 62%).

Summarizing this discussion so far, while networks are widely used and
are productive, there does not seem to exist a strong preference for special-
ization, either at the level of individuals (or firms, defined by industry or
occupation) in terms of searching (or hiring) through networks. In the next
section we will show that, nevertheless, finding a job through social networks
does have an important and independent impact on wages.

4  Empirical Analysis

We are interested in estimating a wage equation of the type

16These results, taken together with the importance of social networks as evidenced in
table 1, seems to lend support to the conclusion that social networks are productive, in
the sense that, when used, they tend to lead to higher offer rates. See Mouw (2003) for
a review and Fernandez, Castilla, and Moore (2000), Fernandez and Weinberg (1997),

17Occupations are classified according to the South African Standard Classification of
Occupations. These are mapped into skill levels using an adaptation of the International
Standard Classification of Occupation due to Ziervogel and Crankshaw (2009) and also
used by Keswell, Girdwood, and Leibbrandt (2012).
\[ W_{ij} = \alpha X_i + \gamma Z_j + \beta (S \ast R)_{ij} + \delta T_{ij} + \theta_i + \varepsilon_{ij} \]  \hspace{1cm} (1)

where \( W_{ij} \) is the log of wage of individual \( i \) in job \( j \) (in Rands per hour), \( X_i \) is a vector of individual characteristics that are valued in the labour market (in this case gender and years of education), \( Z_j \) is a vector of job characteristics (in practice, a vector of industry and occupation fixed effects), \( T_{ij} \) is a vector of time variant characteristics (previous experience and tenure in current job, as well as year fixed effects), and, finally, \((S \ast R)_{ij}\) are our main variables of interest, the interaction between race (African, Coloured and Whites) and the method used to find the specific job under analysis (Relatives, Friends or Formal).

We estimate equation 1 using observations from waves 2, 3 and 4 of CAPS for which we have information on wages, hours worked and the job search method that led to the job.\(^{18}\) There are multiple observations per individual, forming an unbalanced panel. This structure of the data is reflected in the decomposition of the error term in two components, one of which is individual-specific and time invariant (\( \theta_i \)).

We start by estimating equation 1 using a random effects estimator, under the assumption that all the right hand side variables are uncorrelated with the error term, \( \theta_i + \varepsilon_{ij} \). Although this is perhaps a strong assumption, it seems defensible given the nature of our data and the variety of individual and job controls that we can include in the estimation. Additionally, random

\(^{18}\)The CAPS data include a “mega job” table that assigns a unique job number to each job per respondent and records the months in which each job was worked in across waves 2, 3 and 4. We excluded observations from wave 1 of CAPS because the job search variable was coded differently.
effects estimators are more efficient than the fixed effects estimators and this may matter when, as in our sample, there is limited variation across jobs for some of the independent variables of interest (in this case, job search method) which could lead to large standard errors.

The results, for different sets of control variables, corresponding to different assumptions regarding what firms value and can observe, are presented in table 6. In column (1), we present the estimates associated with a simple model where wage depends on job finding method, human capital variables, gender and race. The human capital variables consist of years of education and months of work experience in current and previous jobs, months of occupation and industry-specific experience, and education quality measured through the literacy and numeracy score. Focusing on the coefficients of the interaction between race and job search method, it is immediately obvious that there are two types of penalties (the comparison category is White × formal): firstly, and as expected, Africans receive lower wages than Coloured, who in turn receive lower wages than Whites and, secondly, finding a job through social networks (either relatives or friends) carries an additional wage penalty.

It is possible that job characteristics vary systematically according to search methods, that is, that the wage discounts identified in column (1) simply reflect the nature of the work that social networks connect job seekers with. For that reason, we include a set of industry and occupation fixed effects in the model presented in column (2) (although the estimates associated with these variables are omitted). Finally, in column (3), we also control for individual characteristics such as family background, as proxy
both to characteristics that are potentially valued in the labour market or to the quality of the social contacts to which youth have access to.

It is noticeable that the inclusion of industry and occupation fixed effects does not change our earlier conclusions in any meaningful way (as perhaps would be expected, given the data on job search presented in tables 4 and 5, discussed above). This suggests that the cause of wage penalties is not simply because social networks allocate prospective workers to low paying jobs. The same is not true when considering the estimates presented in column (3): not only are the estimates of the effect of social networks generally much lower, they are no longer statistically significant in the case of White youth. In principle, we would prefer the specification with the larger number of control variables, presented in column (3), particularly given that we are using a random effects estimator and we may worry about problems of correlation between some of the explanatory variables and the error term. However, it is important to note that due to missing values in some of the variables, the inclusion of these variables substantially reduces the sample size.

Although they are not the focus of this analysis, it seems important to notice that the estimates of the effect of education and experience are positive, as expected, and relatively robust to the inclusion of additional covariates. The main surprise is the general lack of importance of the variables measuring individual background, although we must note again the importance of missing values, which reduces the sample size to roughly half the original sample.

As it is known the coefficients of dummy variables in semi-logarithmic
models such as these cannot be directly interpreted. In table 7 we present the wage penalties associated with the race × job search variables using the correction proposed by Halvorsen and Palmquist (1980). We find no evidence that using networks leads to wage premiums, and thus no evidence of the good matches hypothesis. Consistent with the limited choices hypothesis, while more jobs are found through social networks for Africans than for Whites (see table 2 above), this is clearly not because Africans can secure higher wages through social networks. Finally, we notice that, for all races, the coefficients for the ‘relative’ and the ‘friend’ interaction variables are not significantly different to each other. This means that there is no evidence from these results that social distance between referral and referee has an effect on wage.

A fixed effects estimator may still be preferred if the random effects estimates are inconsistent. For that reason, we estimate a fixed effects specification of equation 1

\[ W_{ij} = \theta_i + \alpha X'_i + \gamma Z_j + \beta S_{ij} + \delta T_{ij} + \varepsilon_{ij} \]  

where \( X'_i \) includes those individual characteristics that are valued in the labour market and are time variant, \( S_{ij} \) is a vector of dummy variables indicating the search method, \( \theta_i \) is an individual fixed effect and all other variables have the same meaning as above. The estimates, separate for each race group, are presented in table 8.\(^1\) It is important to notice that these estimates are identified by the existence of changes in successful job search

\(^{1}\)Because race is time invariant, it is not possible to include race and search interaction terms in a fixed effects estimation, as we did in table 6.
strategy, that is, by individuals who had more than one job between 2002-2006 and who found those jobs using different search methods. As shown in table 2, the identifying sample is approximately 1/3 of the total sample.

The coefficients for the main variables of interest (finding a job through friends or through relatives) are presented, as elasticities, in Table 9, again using Halvorsen and Palmquist (1980) correction. Two conclusions emerge from these results. The first is that the use of either friends or relatives carries a penalty in terms of wages. This is true for all race groups, reinforcing our earlier conclusion that there is no evidence to support the good matches hypothesis. Considering that there is much evidence to support positive wage premiums for social network use (Topa, 2011) and that few studies find wage discounts for several major population groups (and not in excess of 10%), this is a significant finding that is broadly consistent with the limited choices hypothesis.

The second conclusion is that, unlike the random effects estimates, the wage penalties associated with the use of relatives as referees are always larger than the penalties associated with the use of friends. The differences are relatively small in the case of Coloured and White youth (as in the random effects estimates) but quite large in the case of African youth. These results suggest that employers may suspect of some degree of opportunistic behaviour from referees and react by discounting the value of the information provided by those referees who are closer to job seekers.
5 Conclusion

It is well known that social networks play a significant role in labour markets in many countries, including developing countries. However, the significance of this fact for labour market outcomes, namely wages, is still not clear. This paper is motivated by two competing hypotheses regarding these effects, the “good matches” hypothesis (which predicts that the use of social networks would lead to higher wages) and the “limited choices” hypothesis (which predicts that wages will be lower or unaffected by social networks when people limit their choices to the jobs available through one’s social networks). We contribute to this discussion by focusing on the motivation of the referee and the possibility that she/he may not select individuals with the highest possible ability - instead privileging individuals who are socially closer. Firms react by offering lower wages.

We use data from the Cape Area Panel Study (CAPS) of South Africa to estimate the wage effect of contact use and of social proximity. Controlling for individual heterogeneity in characteristics that are valued in the labour market (through a range of human capital and family background variables) and also for unobserved heterogeneity (through the use of fixed effects), we show that there are penalties associated with the use of social networks for all race groups, ranging from about 11% - 48%. In addition, for Africans these penalties are compounded by the proximity between job seeker and referee: referrals from relatives carry a very large penalty in contrast to no penalty associated with friends. Interestingly we do not find any convincing evidence of this for Coloureds or Whites. This may reflect either
historical discrimination as an inheritance of apartheid, or different labour market conditions faced by African youth. This result also suggests that if the referred individual is from a disadvantaged group, faced with limited employment choices (as is more likely the case for African youth), then the probability that referees will suggest less capable workers should be higher - and so would be the associated wage penalties imposed by employers.

Lastly, it must be noted that even if contacts lead to lower wages, their use seems to lead to a higher probability of finding a job and avoiding unemployment, which may be especially important in the case of young people who are starting their careers. Hence, our results cannot be interpreted as suggesting that youth should not search for jobs using social contacts. Instead, it would be better if youth had more opportunities to productively use formal search methods. Previous literature (Magruder, 2010) has already argued that social networks may perpetuate inequality across generations in South Africa. In addition to this issue of equity, we have identified an inefficiency in the way workers are matched to employment that results from social network use. Together, these two findings suggest that policy makers should consider ways of further supporting formal job search methods that would facilitate relatively better matches and lessen the prevalence of youth being disadvantaged by limited choices.

References


Magruder, J.R. 2010. “Intergenerational Networks, Unemployment, and Per-


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<th>Variables</th>
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<th>Coloured</th>
<th>Obs</th>
<th>White</th>
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<td>853</td>
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<td>1886</td>
<td>0.29</td>
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<th>White Obs</th>
<th>Observations</th>
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<td>(0.06)</td>
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<td>(0.12)</td>
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<td>0.31 1750</td>
<td>0.11 299</td>
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<td>(0.46)</td>
<td>(0.31)</td>
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<tr>
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<td>(0.07)</td>
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<td>Ind: Construction</td>
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<td>(0.31)</td>
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Standard deviation in brackets
Table 2: Number of individuals by job finding method

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<th>African</th>
<th>Coloureds</th>
<th>Whites</th>
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<td>4</td>
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<td>Found jobs using relatives and formal search</td>
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<td>10</td>
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<td>Found jobs using friends and formal search</td>
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<td>34</td>
<td>95</td>
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<tr>
<td>Found jobs using friends and relatives</td>
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<tr>
<td>Found all jobs using relatives</td>
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<td>171</td>
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<td>Found all jobs using friends</td>
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<tr>
<td>Found all jobs using formal methods</td>
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<td>Total</td>
<td>1132</td>
<td>297</td>
<td>755</td>
<td>80</td>
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<td>(43.4%)</td>
<td>(38.7%)</td>
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Table 3: Current job search method by how last job was found

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<th>Both search methods</th>
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<td>Occ: Skilled agriculture and fishery</td>
<td>22</td>
<td>0.86</td>
<td>0.34</td>
<td>2</td>
</tr>
<tr>
<td>Occ: Craft and related trades workers</td>
<td>476</td>
<td>0.85</td>
<td>0.36</td>
<td>2</td>
</tr>
<tr>
<td>Occ: Plant and machine operators</td>
<td>173</td>
<td>0.83</td>
<td>0.38</td>
<td>2</td>
</tr>
<tr>
<td>Occ: Elementary</td>
<td>648</td>
<td>0.80</td>
<td>0.40</td>
<td>1</td>
</tr>
<tr>
<td>Occ: Other</td>
<td>96</td>
<td>0.74</td>
<td>0.44</td>
<td>1</td>
</tr>
<tr>
<td>Observations</td>
<td>2806</td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Job finding method by industry

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Networks Proportion</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ind: Private households</td>
<td>47</td>
<td>0.79</td>
<td>0.41</td>
</tr>
<tr>
<td>Ind: Agriculture, Hunting, Forestry &amp; fishing</td>
<td>28</td>
<td>0.91</td>
<td>0.29</td>
</tr>
<tr>
<td>Ind: Manufacturing</td>
<td>570</td>
<td>0.81</td>
<td>0.39</td>
</tr>
<tr>
<td>Ind: Electricity, gas and water supply</td>
<td>7</td>
<td>0.52</td>
<td>0.50</td>
</tr>
<tr>
<td>Ind: Construction</td>
<td>239</td>
<td>0.88</td>
<td>0.33</td>
</tr>
<tr>
<td>Ind: Wholesale and retail trade</td>
<td>819</td>
<td>0.67</td>
<td>0.47</td>
</tr>
<tr>
<td>Ind: Transport, storage and communication</td>
<td>62</td>
<td>0.81</td>
<td>0.39</td>
</tr>
<tr>
<td>Ind: Financial intermediation, insurance, real estate</td>
<td>311</td>
<td>0.63</td>
<td>0.48</td>
</tr>
<tr>
<td>Ind: Community, social and personal services</td>
<td>205</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>Observations</td>
<td>2288</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 6: Wages and search method: random effects estimates

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(</td>
<td>(</td>
<td>(</td>
</tr>
<tr>
<td>African x relative</td>
<td>-0.577***</td>
<td>-0.573***</td>
<td>-0.364***</td>
</tr>
<tr>
<td></td>
<td>(0.093)</td>
<td>(0.094)</td>
<td>(0.135)</td>
</tr>
<tr>
<td>African x friend</td>
<td>-0.622***</td>
<td>-0.614***</td>
<td>-0.426***</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.096)</td>
<td>(0.135)</td>
</tr>
<tr>
<td>African x formal</td>
<td>-0.416***</td>
<td>-0.398***</td>
<td>-0.297***</td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td>(0.096)</td>
<td>(0.137)</td>
</tr>
<tr>
<td>Coloured x relative</td>
<td>-0.312***</td>
<td>-0.341***</td>
<td>-0.184*</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>Coloured x friend</td>
<td>-0.347***</td>
<td>-0.363***</td>
<td>-0.161*</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>Coloured x formal</td>
<td>-0.213***</td>
<td>-0.231***</td>
<td>-0.093</td>
</tr>
<tr>
<td></td>
<td>(0.082)</td>
<td>(0.082)</td>
<td>(0.097)</td>
</tr>
<tr>
<td>White x relative</td>
<td>-0.254**</td>
<td>-0.217*</td>
<td>-0.158</td>
</tr>
<tr>
<td></td>
<td>(0.108)</td>
<td>(0.113)</td>
<td>(0.128)</td>
</tr>
<tr>
<td>White x friend</td>
<td>-0.167*</td>
<td>-0.157*</td>
<td>-0.108</td>
</tr>
<tr>
<td></td>
<td>(0.092)</td>
<td>(0.091)</td>
<td>(0.103)</td>
</tr>
<tr>
<td>Male</td>
<td>0.174***</td>
<td>0.142***</td>
<td>0.134***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.026)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Years of schooling</td>
<td>0.067***</td>
<td>0.059***</td>
<td>0.072***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Tertiary education (1 or 2 years)</td>
<td>0.148**</td>
<td>0.136**</td>
<td>0.108</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.067)</td>
<td>(0.074)</td>
</tr>
<tr>
<td>Tertiary education (3 or 4 years)</td>
<td>0.276**</td>
<td>0.268**</td>
<td>0.303**</td>
</tr>
<tr>
<td></td>
<td>(0.129)</td>
<td>(0.124)</td>
<td>(0.155)</td>
</tr>
<tr>
<td>Literacy and numeracy score</td>
<td>0.008***</td>
<td>0.006***</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>First recorded job</td>
<td>-0.144***</td>
<td>-0.090***</td>
<td>-0.066*</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.029)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Experience in current job</td>
<td>0.025***</td>
<td>0.024***</td>
<td>0.021***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Previous experience</td>
<td>0.010***</td>
<td>0.009***</td>
<td>0.009***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Experience in same occupation</td>
<td>0.004***</td>
<td>0.003*</td>
<td>0.005*</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Experience in same industry</td>
<td>-0.015***</td>
<td>-0.011***</td>
<td>-0.010***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Urban</td>
<td>0.056</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Family background: well-off</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.071</td>
</tr>
<tr>
<td>Family background: ok</td>
<td></td>
<td></td>
<td>-0.100*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.061)</td>
</tr>
<tr>
<td>Mother’s education</td>
<td></td>
<td>0.011</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>Father’s education</td>
<td></td>
<td>0.011*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.006)</td>
<td></td>
</tr>
</tbody>
</table>

Observations: 2,154
Number of respondents: 1,406

Robust standard errors in parentheses. An interaction variable for “already working at start of CAPS” x “previous experience”, time dummies, and a constant were included but not reported. Occupation and industry dummies were included in (2) & (3) but are not reported. *** p<0.01, ** p<0.05
### Table 7: Wages and search method: random effects estimates

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>African x relative</td>
<td>-0.438***</td>
<td>-0.436***</td>
<td>-0.305***</td>
</tr>
<tr>
<td>African x friend</td>
<td>-0.463***</td>
<td>-0.459***</td>
<td>-0.347***</td>
</tr>
<tr>
<td>African x formal</td>
<td>-0.340***</td>
<td>-0.328***</td>
<td>-0.257**</td>
</tr>
<tr>
<td>Coloured x relative</td>
<td>-0.268***</td>
<td>-0.290***</td>
<td>-0.167***</td>
</tr>
<tr>
<td>Coloured x friend</td>
<td>-0.286***</td>
<td>-0.304***</td>
<td>-0.149***</td>
</tr>
<tr>
<td>Coloured x formal</td>
<td>-0.192***</td>
<td>-0.208***</td>
<td>-0.089</td>
</tr>
<tr>
<td>White x relative</td>
<td>-0.224**</td>
<td>-0.195*</td>
<td>-0.146</td>
</tr>
<tr>
<td>White x friend</td>
<td>-0.154*</td>
<td>-0.145*</td>
<td>-0.102</td>
</tr>
<tr>
<td>Observations</td>
<td>2,154</td>
<td>2,154</td>
<td>1,638</td>
</tr>
<tr>
<td>Number of respondents</td>
<td>1,406</td>
<td>1,406</td>
<td>1,043</td>
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</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.10

### Table 8: Wages and search method: fixed effects estimates

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative</td>
<td>-0.645***</td>
<td>-0.161**</td>
<td>-0.361**</td>
</tr>
<tr>
<td>Friend</td>
<td>-0.120</td>
<td>-0.135*</td>
<td>-0.347***</td>
</tr>
<tr>
<td>Years of Education</td>
<td>-0.018</td>
<td>0.013</td>
<td>0.001</td>
</tr>
<tr>
<td>First recorded job</td>
<td>-0.326*</td>
<td>-0.141***</td>
<td>0.074</td>
</tr>
<tr>
<td>Experience in current job</td>
<td>0.043***</td>
<td>0.016**</td>
<td>-0.011</td>
</tr>
<tr>
<td>Previous experience</td>
<td>-0.026</td>
<td>0.013*</td>
<td>-0.006</td>
</tr>
<tr>
<td>Experience in same occupation</td>
<td>0.045***</td>
<td>0.007**</td>
<td>0.005</td>
</tr>
<tr>
<td>Experience in same industry</td>
<td>-0.066***</td>
<td>-0.008**</td>
<td>0.005</td>
</tr>
<tr>
<td>Observations</td>
<td>426</td>
<td>1,521</td>
<td>221</td>
</tr>
<tr>
<td>Number of respondents</td>
<td>328</td>
<td>941</td>
<td>147</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. An interaction variable for “already working at start of CAPS” x “previous experience”, time dummies, industry and occupation dummies and a constant were also included but are not reported.

*** p<0.01, ** p<0.05
Table 9: Wages and search method: fixed effects estimates

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>African</td>
<td>Coloured</td>
<td>White</td>
</tr>
<tr>
<td>Relative</td>
<td>-0.475***</td>
<td>-0.148**</td>
<td>-0.303**</td>
</tr>
<tr>
<td>Friend</td>
<td>-0.113</td>
<td>-0.126*</td>
<td>-0.293***</td>
</tr>
<tr>
<td>Observations</td>
<td>426</td>
<td>1,521</td>
<td>221</td>
</tr>
<tr>
<td>Number of respondents</td>
<td>328</td>
<td>941</td>
<td>147</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.10