Chapter 4

How does additional education affect willingness to work in rural remote areas? An application on health workers in a low-income context

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An application on health workers in a low-income context

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Abstract

The main objective of this paper is to evaluate the effect of offering educational opportunities as a strategy to recruit health workers to rural areas. Tanzania, like the rest of sub-Saharan Africa, has a very small and unequally distributed health workforce. It has been suggested that rural remote jobs can be made more attractive to health workers with basic clinical skills by offering them the opportunity to upgrade their skills after a certain period of service. A data set capturing stated job preferences among freshly educated Tanzanian health workers with basic and more advanced clinical education is applied in order to investigate how additional education as an incentive mechanism affects willingness to work in rural areas. In order to control for selection effects into the additional education scheme, the two cadres are matched on propensity scores. It turns out that those health workers with advanced clinical education would have been more likely to prefer a job in a rural remote area had they not received the advanced clinical education. This effect (the ATT) is significant and substantial with several different specifications. The result is robust with regards to omitted variables and goes a long way in suggesting that a policy aimed at recruiting health personnel with basic clinical education to rural remote areas by offering jobs that include possibilities of upgrading after a certain period of service may be a temporary measure only.

Keywords: Education, Propensity Score Matching, Human Resources for Health, Mobility

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1. Introduction

The objective of this paper is to evaluate the effect of offering educational opportunities as a strategy to recruit health workers to rural areas. In particular, it focuses on gaining knowledge about the effect of upgrading from basic to advanced clinical education on willingness to work in rural remote areas; however, it also investigates the relationship between a broad range of personal characteristics and willingness to work in rural remote areas. For these purposes, a data set capturing the stated job preferences of Tanzanian clinical officers (COs)[2] and assistant medical officers (AMOs)[3] is applied.

The Tanzanian health workforce is small even in an African context (Joint Learning Initiative, 2004), and unequally distributed between urban and rural areas (Munga and Mæstad, 2009). The most comprehensive overview of the available evidence on human resources for health (HRH) in Tanzania (Dominick and Kurowski, 2005) identifies the geographical imbalance as one of five main HRH problems in the Tanzanian health system. This imbalance represents a serious problem when it comes to delivering crucial health services to a large share of the population. Health systems all over the world, particularly in low-income countries, face similar challenges.

Thus it is established that there is a need to recruit more health workers to rural areas and to rural remote areas in particular, but there is very little quantitative evidence of what kind of policy could actually be successful in doing so. Kolstad (2010) studied the structures of job preferences of fresh COs in Tanzania and used them to discuss potential strategies for attracting COs to rural remote areas. This particular group of COs expressed a strong preference for jobs with prospects of obtaining more education; it was thus concluded that rural remote jobs would be found more attractive if they offered an opportunity to obtain more education after a certain period of service. From other low-income countries also we know that opportunities for educational upgrade, career development, and colleagues in the workplace are motivating factors that have been found to be important when health workers decide where to work (Serneels et al., 2005). Similarly, Vujicic et al. (2004) show that the prospect of an opportunity to upgrade a worker's qualifications is an important factor behind the choice of work location.

[2] A clinical officer is a health worker with three years of education, like nurses but more clinically oriented.
[3] An assistant medical officer is a CO with two years of additional education.

Education can have a direct positive impact on income, health, and so on for the individuals that obtain it, but it may also give positive externalities to these individuals' local environment—*e.g.*, in the form of higher tax income, more informed decision making, and awareness of health promotion. It thus appears wise to attract COs to rural remote areas by offering them opportunities to upgrade to AMOs after a certain period of service. There may be one serious drawback with offering more education to COs, however: it is unclear what the long-term implications will be. It has been argued that attainment of higher-level education tends to open up new opportunities in the labour market (McCormick, 1997). The long-term effect of the proposed policy will depend on where these opportunities are located. Knowing that jobs requiring higher education are often located in more central areas, such new opportunities may lead to movement towards those central areas.[4] Thus, recruitment and retention of AMOs may become even more difficult than recruitment and retention of COs.

Should policy makers in Tanzania worry about this? A first step towards answering such a question is to analyse the stated job preferences of the two groups of health workers. The remainder of this paper is structured as follows: section 2 provides background information about willingness to work in rural areas and the link between education and mobility in those areas. Sections 3 and 4 describe the applied data and empirical strategy, while section 5 presents the results. Section 6 includes a sensitivity analysis and, finally, section 7 offers concluding remarks.

2. Background

2.1 Willingness to work in rural areas

From a policy maker's point of view, mobility is a prerequisite for reallocating human resources, such as knowledge and competence, to where they are most needed and where welfare gains are highest.[5] In essence, the problem of recruiting and retaining health personnel in rural remote areas of Tanzania is a mobility problem. In the general literature on labour

[4] Note that there are no formal differences in the wages of AMOs employed in urban and rural areas.
[5] Such allocations could be either voluntary or mandatory. A voluntary policy of allocating human resources efficiently is typically to design incentive systems that make it profitable for health workers to choose a job in an area where the authorities would like them to work. A policy based on less voluntarism could be to implement mandatory periods of service at a location chosen by the authorities. The first policy is more dependent on mobility than the second.

mobility, suggested reasons for differences in mobility are primarily differences in moving costs (Bentivogli and Pagano, 1999); these could be direct, such as losses due to house price differentials (Oswald, 1999, Belot and Ederveen, 2005), or indirect, such as the loss of local social networks (David et al., 2008a, David et al., 2008b). Moreover, local welfare systems have been reported to be restrictive to regional mobility (McCormick, 1997). In the specific context of the geographic imbalance of health personnel in low-income countries,[6] another explanation could be that pull-factors like job characteristics or the environment in rural remote areas are not conducive. An overview of some the pull-factors and their power to attract fresh COs to rural remote areas in Tanzania is provided in Kolstad (2010).

In addition to regional circumstances affecting mobility, some have pointed out that personal characteristics have an important direct effect on the decision to migrate (Antolin and Bover, 1997). Most general research on labour mobility has concentrated on regional push and pull factors (see e.g. Belot and Ederveen, 2005, Bentivogli and Pagano, 1999, Decressin and Fatas, 1995, Gregg et al., 2004), while studies of geographical imbalance typically focus on individual characteristics and motivational issues associated with the propensity to work in rural areas (see e.g. Serneels et al., 2005, León and Kolstad, 2010, Mangham, 2006, Matsumoto et al., 2005). Antolin and Bover (1997) argue that there are important interaction effects between individual and regional characteristics in addition to the direct effect of individual characteristics. Transferred to the research problem of this paper, this means that individual propensities to take a job in a rural remote area will also affect response to recruitment and retention policies, such as offering education after a certain period of service. Thus, depending on individual characteristics, two individuals with the same initial expressed willingness to work in a rural area may respond differently to the same recruitment policy.

Several empirical studies show that individual characteristics are strongly related to individual propensity to work in rural remote areas. Chomitz et al. (1998) report that the premium needed to make Indonesian health workers move to rural districts was substantially lower for students from rural districts than for students originally from Jakarta. In line with this, several studies have shown that the presence of family members or other links to rural and remote areas increases an individual's probability to consider these areas for clinical practice (Dussault and Franceschini, 2006, British Columbia Medical Association, 1998, Matsumoto

[6] The same argument can be proposed for high-income countries; however, the contrast between rural remote and more central areas is often greater in low-income countries.

et al., 2005, Kolstad, 2010). Furthermore, a Japanese study found that men were much more likely to remain in rural practice than women (Matsumoto et al., 2005). This finding is supported by a study observing that women are less likely to accept rural posts and are accordingly underrepresented in rural areas (Doescher et al., 2000). Other evidence shows that nurses in Malawi are more likely to work in rural districts if decent housing is offered (Mangham, 2006), which it is normally not, and finally that age sometimes matters as well: younger individuals typically have fewer family responsibilities and lower moving costs (Chomitz et al., 1998, Serneels et al., 2005).

Other identified determinants of location decisions can be classified as motivational factors rather than mere demographics. Intrinsic motivation or, to be exact, a proxy in the form of a measure of willingness to help the poor has been found in one study to be one of the most successful variables in explaining willingness to work in rural areas (Serneels et al., 2005). Kolstad (2010) follows up on this and shows that COs very willing to help the poor respond differently to incentives to take up rural posts than do those not so willing to help the poor.

2.2 Mobility and education

Given that most students at both the CO and the AMO training programs have an urban background, mobility is an important prerequisite for the recruitment of more health workers to rural and rural remote areas. It has been argued that attainment of higher-level education tends to open up new opportunities in the labour market (McCormick, 1997) and thus to increase mobility; still, the empirical literature focusing on mobility has not been particularly concerned with the effect of education. Among the few studies that touch upon this, directly or indirectly, the general finding is that education is positively related to observed mobility. For instance: having higher education more than doubled the probability of migration in a study of regional migration in Spain (Antolin and Bover, 1997). In the same study, people with only primary education were found to be less likely to migrate. U.K. employment rates have been stable for the highly educated between 1979 and 1999 relative to those of the comparatively less educated, which has been interpreted to suggest that those with higher education are more mobile (Gregg et al., 2004). Machin et al. (2008) show that in particular the employment rates of those with tertiary educations have converged over the studied period across regions in Norway; they argue that regional mobility is strongly correlated with labour market events: those changing jobs also move across regions, and vice versa. They further report that increased compulsory education[7] increases the probability of being employed in a large town, an indication of a kind of 'one-way-mobility' toward central areas. Thus, mobility seems to increase with education, but for policy makers concerned with the geographical distribution of services and of the workforce this increased mobility can be a two-edged sword.

Is this mobility good or bad news for those concerned with recruiting health workers to rural areas? As education is positively related to mobility, this could mean two things for willingness to work in rural areas: on one hand it could mean that the health workers have more knowledge and are considered more relevant workers for a variety of jobs, thus having more possibilities to work where they would actually like to. This would be positive for the rural areas, provided they offer interesting jobs requiring AMO-level skills. Unfortunately, however, this is seldom the case in low-income countries such as Tanzania, and particularly seldom in those countries' remote areas. Many of the COs that pursue additional AMO studies already work in rural areas (Munga and Mæstad, 2009).[8] If, by obtaining education, these health workers also get more job opportunities and become more mobile, it seems likely that at least some will migrate to more central areas. Increased mobility thanks to additional education could thus also lead to a brain drain, especially from the rural remote areas.

Some of the factors that have been identified as related to willingness to work in rural remote areas can simultaneously affect the decision to pursue AMO studies. It is thus an empirical challenge to disentangle selection effects from the direct effects of additional education on willingness to work in rural remote areas. To our knowledge, only two studies try to single out the causal effect of education on mobility (Machin et al., 2008, Malamud and Wozniak, 2008), both by an instrumental variable approach. The studies use different data sets and instruments, and focus on different levels of education, but both conclude that education leads to increased mobility. This study takes another approach by using propensity score matching between individuals studying to be COs and individuals studying to be AMOs, in order to correct for differences related to selection into AMO studies. Propensity score matching

[7] Based on a school reform where basic mandatory education increased from 7 to 9 years, the so-called *ungdomsskolereformen*.
[8] In the applied data set in this paper, 21.50 % of the AMO students came from CO jobs in rural remote areas.

reduces the number of control variables by incorporating them into one index, the propensity score, as well as by allowing the researcher to control for confounding factors.[9]

3. Data

3.1 The data set

An extensive survey was administered to more than 300 final-year students training to be clinical officers (COs), and to 120 final-year students training to be assistant medical officers (AMOs). For COs wanting to upgrade their qualifications, the AMO grade is the natural way to go. Mid-cadres like COs and AMOs represent a large and important share of the health workforce in Tanzania (9.5%, compared with 1.1% for medical doctors (Kurowski et al., 2004)), and in practice COs form the backbone of the clinical workforce, in rural areas especially. Moreover, COs' university qualifications are not often recognised in high-income countries; as a result, they are more likely to stay in their home country than are other cadres (*e.g.* medical doctors and nurses). It is thus important and relevant to study the job preferences of these groups. This survey collected information on demographics and a wide range of other background characteristics among health workers. Attitudes and preferences concerning the practice of clinical work and the motivations for being a health worker were also included.

The data were collected during the autumn of 2007. Participation in the research was voluntary, and the participants were not compensated in any way. Some 320 CO finalists and 120 AMO finalists (around 60% of all CO finalists and 80% of all AMO finalists in Tanzania) from 10 and 3 randomly selected schools,[10] respectively, participated. All finalists in the selected schools were invited to participate. The data were collected mostly during school time, on school premises; this largely explains the unusually high response rate of around 96%. Questionnaires that were not completed or that were filled out by respondents from countries other than Tanzania were excluded from the sample; thus the final sample comprised 294 CO respondents and 118 AMO respondents.

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[9] Angrist, J. D. and Hahn, J. (2004) show that even though there is no asymptotical efficiency gain from the use of estimators based on propensity score, there will often be a gain in precision in finite samples because of the reduction of the dimensions of the analysis. However, when applying propensity matching, the researcher uses prior knowledge to determine which factors to include in the propensity score, and it is ultimately his or her willingness to impose restrictions on the score (as all possibly relevant factors cannot be observed, it is not possible to include them in the score) that gives propensity score-based inference its conceptual and statistical power.

[10] Appendix A.1 provides a list of the schools and a description of the selection procedure.

Both the CO and AMO training centres are obliged to recruit students from all over Tanzania; within each cadre there are no systematic differences between students at the different schools.[11] Thus the sample is likely to be representative of the two particular groups of health workers studied.

3.2 Descriptive statistics

From Table 1, we can observe significant initial differences between the two groups'[12] willingness to work in rural remote areas. COs are 13 percentage points more likely to prefer a job in a rural remote area than are AMOs, before we control for selection; AMOs have a 15.9% probability of preferring a rural remote job, while the probability of COs preferring a rural remote job is almost double, 28.8%.

Turning to personal characteristics, we find around 35% females in both groups. Among the COs, 58.1% were single, while among the AMOs only 16% reported being single, implying that the two groups are in somewhat different life situations. This impression is reinforced by a look at the responsibility for dependents (own children, parents, relatives, etc.): only half of the COs responded that they had one or more dependents, while 97% of the AMOs reported the same. There is also a bias with respect to background; those with urban backgrounds are more likely to seek additional education. The two cadres appear to be ambitious, although the COs seem significantly more so than the AMOs. About 20% in both groups are strongly motivated to help others; moreover, the COs have a slightly stronger professional interest than do the AMOs.

(Table 1 around here)

[11] However, there may be systematic differences between the two cadres.

[12] Fourteen observations were excluded from the analysis because the outcome variable was missing. Observations with missing data for the included independent variables were also excluded, resulting in 388 observations in total. The data set then consisted of 281 COs (controls) and 107 AMOs (treated).

4. Empirical strategy

4.1 Regression analysis

The regression model is given by the following equation:

$$Pr(Y_i = 1) = \beta\, amo_i + \mu\, demo_i + \delta\, motivation_i + \varepsilon_i, \qquad (1)$$

where Y_i is a dummy variable indicating whether individual i prefers a job in a rural remote area, amo_i is a dummy variable indicating whether or not individual i is studying to become an AMO, $demo_i$ is a vector of demographic control variables, $motivation_i$ is a vector of motivational control variables, and ε_i is a random error term capturing the unobserved. β is the marginal effect of the AMO variable, and μ and δ are vectors of marginal effects for the demographic and motivational control variables.

The dependent variable is taken from a question in the survey where respondents were asked where they would prefer to work after finishing their studies. As a follow-up, they were asked if this place was located more than a three-hour bus ride from the district headquarters, which is our definition of a rural remote area. If yes, the dummy variable took the value 1; if no, it took the value 0. Standard binomial probit regressions were thus run in order to investigate the relationship between willingness to work in rural remote areas and the three groups of covariates. Marginal effects after probit were calculated as an average of the individual marginal effects, using the delta method.

Demographic variables include sex, whether or not an individual is single, whether or not an individual has dependents and whether or not the parents of an individual live in a rural remote area. The questionnaire also allowed for some relevant motivational variables: the first is a dummy capturing whether or not the student has ambitions to become an in-charge. Furthermore, since students who are very willing to help other people have been found to react differently to incentives (Kolstad, 2010), a dummy variable measuring willingness to help other people was included. The dummy was constructed on the basis of *total* agreement to *all* of the following statements: 1) ‘I feel good when I can help other people, even if it means I have to work very hard’; 2) ‘The general satisfaction coming from helping other people is the same no matter what I get paid’; and 3) ‘As long as I receive the minimum public salary for COs, I am willing to work where most needed in order to help as many as possible'. Finally, the regressions included a dummy indicating whether or not a respondent had a strong professional interest. The dummy was constructed similarly to the one for willingness to help the poor: it was positive (=1) if there was total agreement to both of the following statements: 1) 'A low salary can be compensated by a professionally interesting job' and 2) 'It is important that there be availability of relatively advanced equipment for the job to be interesting' *and* the ranking of the 'equipment and drugs situation' at a facility as number 1 or 2 of importance when choosing where to work.[13]

4.2 Isolating the effect of additional education on willingness to work in rural remote areas

In Tanzania, COs normally gain additional education and become AMOs after a period of practice as COs. Thus, in contrast to other studies focusing on the link between education and mobility (e.g. Machin et al., 2008, Malamud and Wozniak, 2008, McCormick, 1997), we are not using a continuous period of education but rather studying the effects of a discrete change in education level.

Since the applied data set is not experimental (it is not random who is in the CO group and who in the AMO group), we must be careful when evaluating the effect of advanced clinical education on willingness to work in rural remote areas. As with all non-experimental data, there is reason to believe that we have a biased sample that may lead to a confounding between the effect of becoming an AMO and the factors leading to an individual's choice to become an AMO. In the regression analysis in section 4.1 we tried to control for confounding factors by including them directly in the analysis; however, since the two cadres display not only substantial differences in means but also in the distributions of confounding variables, there is for some variables, such as age and number of dependants, little overlap between the distributions. In essence, then, regression analysis projects behaviour of individuals in one cadre outside the observed range to form a comparison for individuals in the other cadre. Such projections will necessarily be highly sensitive to functional form. In the following, the two cadres are matched on propensity scores in order to minimise the relevant differences between

[13] Participants were asked to rank seven job characteristics according to importance for their choice of job: salary and allowances, possibilities for upgrade of qualifications, infrastructure in the area, the drugs and equipment situation at the health facility, workload, and location.

them and identify the causal impact of additional clinical education on willingness to work in rural remote areas of Tanzania.[14]

When performing the propensity score matching, we tried to assess whether there is a difference between where AMO students report preferring to work and where they would have preferred to work if they had not had the chance to pursue AMO studies. This effect is given by:

$$\Pr\left[Y_i^{AMO} = 1 \middle| amo = 1\right] - \Pr\left[Y_i^{CO} = 1 \middle| amo = 1\right] \tag{2}$$

where Y_i^{AMO} is a dummy indicating preference for a job in a rural remote area for individual i as an AMO student, and Y_i^{CO} is a dummy indicating preference for a job in a rural remote area for individual i as a CO student. The average of the individual effects is frequently referred to as the average treatment effect on the treated (ATT).[15] Because it is never possible to observe both states for the same individual at the same time, the challenge is to find a suitable way to estimate the counterfactual.

The descriptive statistics in section 3.2 showed significant differences between the AMOs and COs, indicating that the AMOs form a selected group. Hence, replacing the average outcome for the COs as the counterfactual (the second term in equation 2) will necessarily lead to biased estimates. However, one way around this is to use observed outcomes for the treated group, the AMO students in this paper, and some kind of matching estimator for the counterfactuals. Propensity score matching offers a solution to this by matching individuals with similar observable characteristics. Dehejia and Wahba (2002) show that propensity score matching can yield accurate estimates of the treatment effects in non-experimental settings in which the treated group differs substantially from the control group (Dehejia and Wahba, 2002). It is, however, important that the conditions for a good match are met if the propensity score matching is applied on such a sample. Possibly the most fundamental is the

[14] Other common ways to control for selection bias are diff-in-diff and instrument variable approaches. The applied data is cross-sectional; hence a diff-in-diff analysis was not possible. Moreover, there are strict conditions for good instruments, and we were not able to find a suitable instrument for a robust analysis of the effect of additional education on willingness to work in rural remote areas.

[15] For a discussion of the relevance of the ATT measure, see Heckman et al. (1999). Note that by focusing on the effect on the treated only, we are unable to make inferences about the whole population. The coefficients for the *amo* variable in the regression analysis, however, can be seen as the general average treatment effect (ATE).

unconfoundedness condition[16]: the outcome, Y_i, should be independent of whether or not a person is treated (studying to be an AMO) when we have controlled for the covariates not affected by treatment (*demo & motivation*), in the following called X_i, so that $Y_i \perp amo_i \mid X_i$. This means that exposure to treatment (studying to be an AMO) should be random among individuals who have the same X value. Second, in order for the estimates not to be model-dependent, we restrict estimation to the common support area where, given the covariates, X, all individuals have a positive probability both of receiving treatment and not receiving treatment[17]; $0 < Pr(amo_i = 1 \mid X_i) < 1$. If there is not a positive probability of being in both groups, the regression models have to extrapolate counterfactual outcomes to areas outside the common support, meaning that estimates of the counterfactuals will be model-dependent.

The propensity score, $p(X_i)$, is the probability of receiving the treatment (studying to be an AMO), given certain covariates, X_i.

$$p(X_i) = E(\, amo_i \mid X_i \,) = Pr(\, amo_i = 1 \mid X_i \,) \tag{3}$$

The outcome is independent of amo_i once we have controlled for the propensity score, so that $Y_i \perp amo_i \mid p(x_i)$ (Rosenbaum and Rubin, 1983).

Assuming that both the independency and the minimal overlap conditions hold, the propensity score estimator for ATT can be written like this:

$$ATT_{ps} = E_{p(X)|amo=1}\left(\Pr\left[Y^{AMO} = 1 \mid amo = 1, p(X)\right] - \Pr\left[Y^{CO} = 1 \mid amo = 1, p(X)\right]\right) \tag{4}$$

where the outer expectation is over the distribution of the propensity score.

With propensity score matching, we try to correct for selection bias stemming from observed characteristics. Hence, the matching should lead to a balanced sample that ensures that the relevant observable differences between the groups are minimised (Ho et al., 2007). In order to check that the sample is indeed more balanced after matching, we compare the normalised

[16] See Rosenbaum and Rubin (1983) for a proof.
[17] This is often referred to as the minimal overlap condition.

difference in means of each covariate, $\bar{x}$, between the AMOs and the COs before and after matching.[18] The normalised difference is given by:

$$StDiff = \frac{\bar{x}^{AMO} - \bar{x}^{CO}}{\sqrt{(Var(x^{AMO}) + Var(x^{CO})}} \qquad (5)$$

We would like the difference to be as small as possible after matching, but normally a normalised difference below 0.25 is considered small enough.

When there are few comparison units left after discarding the irrelevant comparison units, the choice of matching algorithm matters (Dehejia and Wahba, 2002). The estimated ATT may be very sensitive to the applied matching algorithm when the data set is not so big and when there are relatively few matches. In order to check that the choice of matching algorithm is not driving the results, we thus apply four: nearest neighbour matching, radius matching, stratification matching and, finally, Kernel matching.[19]

Included covariates are the same as those used in the straightforward regression analysis, with one exception: age is excluded from the matching analysis. The reason for this is that the AMOs are necessarily older than COs, as one must become a CO and gain experience before starting AMO studies. It was thus very difficult to match the groups on this variable. However, by controlling for dependents, civil status, ambitions to become in-charge, and willingness to help others, we hope to cover the most important effects related to age.

5. Results

5.1 Regressions

Regression results for variations of equation 1 are shown in Table 2. The first thing that springs to mind when looking at the table is that, in all specifications, studying to be an AMO is negatively related to the expressed preference for working in rural remote areas. The relationship is significant at a 1% level. Depending on the specification, being an AMO

[18] The pscore command in Stata, applied in the analysis, uses a slightly different approach to checking for balance; see Becker and Ichino (2002).
[19] For a description of the matching algorithms and a brief discussion of weaknesses and strengths, see Becker and Ichino (2002). All matching methods are applied and corresponding ATTs are derived using the available pscore command (attnd, attr, atts, attk) in Stata.

student lowers the probability of preferring to work in a rural remote area by between 12.9 and 15.7 percentage points. Having controlled for observable characteristics, the negative effect of becoming an AMO on willingness to work in rural remote areas is thus more or less unchanged.

(Table 2 around here)

Among the demographic variables, only one was significantly related to willingness to work in rural remote areas: unsurprisingly, it turns out that having parents living in a rural remote area increases the probability of preferring a job in such an area by around 28 percentage points. The result is significant at a 1% level in both specifications where the variable is included.

It is interesting to note indications in the data that motivational factors matter in where the students prefer to work. Having a strong professional interest is positively related to the preference for a rural remote job. This could reflect the common perception that mid-cadres like COs and AMOs are given more autonomy and more challenging tasks in rural health facilities, compared to urban settings where there are more 'real' doctors around. Furthermore, having ambitions to become an in-charge is negatively related to preference for a job in a rural remote area. Note that in Table 1 the COs were both more willing to work in rural remote areas and more eager to become in-charges; there is reason to worry about endogeneity if those more willing to work in rural remote areas automatically tick off that they want to become in-charges as well, since this is how they expect the rural remote job to be. However, in the regression analysis, we do observe a negative relationship between preferences for becoming an in-charge and for jobs in rural remote areas. It thus seems there is no reason to worry strongly about endogeneity.

The predicted probability of preferring a job in a rural remote area was, depending on the specification, estimated to be between 25.14% and 25.26%.

5.2 The effect of additional education

5.2.1 A closer examination of the effect of education

The probit regression that forms the basis of the propensity score is displayed in Table 3. The dependent variable is the dummy indicating whether or not an individual is an AMO student. We recognise many of the patterns observed in the descriptive statistics; single students are significantly less likely to be AMO students, while those with dependents are significantly more likely to be AMO students. These findings reinforce the impression that the two groups are in somewhat different life situations; controlling for this will be important. Moreover, students with rural backgrounds (parents living in rural remote areas) are less likely to be AMO students. The same goes for students with strong professional interests and ambitions to become in-charge.

(Table 3 around here)

As explained earlier, the propensity score is the predicted probability (based on the probit-regression) of belonging to the AMO group given the chosen covariates. Before we restrict the observations to the common support area, the mean probability of being in the AMO group for the CO group is 20%, while for the AMO group it is 47%. The balance requirement was met, ensuring that within each of four different strata observations with the same propensity score were randomly 'assigned' to being CO students and AMO students.[20] Figure 1 gives a graphic presentation of the propensity scores for the two groups in the common support region.[21] We observe that COs are distributed more evenly according to propensity score than are AMOs, and that they have a lower mean propensity score (0.39 compared to 0.48). However, we also notice that the means are closer to each other now than they were in the sample not restricted to the common support area.

(Figure 1 around here)

[20] This implies that the distribution of propensity scores of the COs and AMOs is on average observationally identical within each strata.
[21] The common support area ensuring minimal overlap was selected by the Stata pscore-algorithm to be [.05842 - .75016].

5.2.2 Descriptive statistics, common support

Table 4 shows the summary statistics for the covariates in the two groups after restricting the analysis to the common support region. The statistics for the treatment group, the AMOs, are the same as in Table 1, but those for the control group, the COs, have changed as we have restricted the sample to the common support region. This leads to more similar statistics for the two groups than those observed in Table 1. Some important changes should be noted: first, 134 observations from the control group were discarded. Second, the fraction of single COs is now more similar to the fraction of single AMOs, with only 27.2% of the former being single; furthermore, 93% of the COs have one or more dependent, making the difference now only significant at a 10% level. The fraction of COs with parents living in rural remote areas is slightly higher compared to the fraction of AMOs than it was for the sample not restricted to the common support area. The fraction with strong professional interest is still higher among the COs than among the AMOs, although this difference is now less significant. In general it can be noted that the differences between the groups are less significant in the sample restricted to the common support area.

(Table 4 around here)

Another way of assessing whether the two samples have become more similar is to study the normalised difference in means both before and after restricting to the common support area. The normalised differences in means, sometimes called the standardised bias, are shown in Table 5.

(Table 5 around here)

It turns out that when the variation in the two groups is taken into consideration, the variables that are most biased before we prune the sample are the single-dummy, the dependents-dummy, and to some extent the dummy capturing ambitions to become an in-charge. After pruning, the bias is generally reduced for the covariates that caused some worry before pruning, ensuring that the bias of all included covariates is well below 0.25 in the sample restricted to the common support area. Although there still is some bias in the sample, we should be able to trust the estimates of the ATT to a relatively high degree within the common support area.

5.2.3 ATT

Table 6 shows the ATTs calculated with the different matching methods. With all matching methods, a negative and statistically significant average effect on the treated emerges. When the difference between the two health worker groups is accounted for, the AMOs are found to have, depending on the matching algorithm used, a probability between 0.15 and 0.20 percentage points lower of preferring a job in a rural remote area after their studies. The difference is thus likely to be even higher than it initially appeared in Tables 1 and 2.

(Table 6 around here)

The difference between the matching algorithms is interesting; the nearest neighbour algorithm gives the lowest ATT, but at the same time produces the highest standard error. This may be due to the fact that there is only one match for each treatment observation, and that only 118 control observations are used. The other ATTs are more similar to one another; they all make use of more information by including more observations when matching. There is, however, a trade-off between lower variations on one hand and biased estimates on the other (if many observations are used several times); hence, we are not able to conclude that one estimate is more correct than the other.

6. Sensitivity analysis

An omitted variable can cause biased estimates if it simultaneously affects selection into AMO studies and willingness to work in rural areas. The problem of omitted variables is thus not avoided by the propensity score matching performed in section 5.2. One consequence of this is that we should be able to match on those observable covariates that we have reason to think may create a biased sample; another is that we are able to argue that these are actually the covariates of interest for our research question, that we have not left out any covariates of believed importance from the analysis. In practice, however, due to limited access to all relevant data, it is seldom possible to ensure that we have included all relevant variables. A sensitivity analysis focusing on the effect of possibly omitted variables on the estimates of treatment effects is thus applied.

The test is based on the solution originally suggested by Rosenbaum (2002)[22]; the aim is to determine how strongly an omitted variable must influence the selection process to undermine the implications of the matching analysis (Becker and Caliendo, 2007).

Assume that the probability of individual *i* of being in the AMO group is given by the observed covariates X_i, and any unobserved variable u_i. For simplicity, we assume that u_i is a dummy variable taking the value 0 or 1. The probability of individual *i* of being in the AMO group can thus be written as:

$$P_i = Pr(amo_i = 1 \,/\, X_i, u_i) = F (\eta X_i + \gamma u_i) \qquad (6)$$

where η is the effect of the propensity score, γ is the effect of the unobserved covariate, and F indicates a logistic distribution. It can furthermore be shown that the odds ratio of two individuals *i* and *j* ending up in the AMO group is given by:

$$\frac{P_i(1-P_j)}{P_j(1-P_i)} = \frac{\exp(\eta X_i + \gamma u_i)}{\exp(\eta X_j + \gamma u_j)} = \exp[\gamma(u_i - u_j)] \qquad (7)$$

The last equality holds as long as the two individuals have identical observed covariates, or, in the case of propensity scores matching, identical propensity scores. When there are no differences in unobserved variables between the matched individuals, so that $u_i - u_j = 0$, or when unobserved variables have no influence on the probability of being in the AMO group so that $\gamma = 0$, the odds ratio equals one. Odds ratios above one indicate that there is bias caused by omitted variables. Rosenbaum (2002) shows that (7) implies the following bounds on the odds ratio of either of two matched individuals being in the AMO group:

$$\frac{1}{e^{\gamma}} \leq \frac{P_i(1-P_j)}{P_j(1-P_i)} \leq e^{\gamma} \qquad (8)$$

When $e^{\gamma} = 1$, the two persons have the same probability of being in the AMO group. When $e^{\gamma} > 1$, two persons with identical propensity scores have different odds of being in the AMO

[22] The technicalities of the test are described in Becker and Caliendo (2007) and the test is applied by using their mhbounds-command developed for Stata users. Substantial parts of the presentation of the sensitivity analysis are based on Becker and Caliendo (2007).

group,[23] implying an omitted variable bias in the estimates. The sensitivity analysis focuses on when such a bias alters the estimated treatment effect. In order to be significant, the treatment effect has to cross some kind of test statistic. Aakvik (2001) suggests using the non-parametric Mantel Haenszel statistic, Q_{MH}, when the outcome variable is a dummy. The Q_{MH} measures the number of students in the AMO group that prefer to work in a rural remote area compared to the predicted number of students that would prefer to work in a rural remote area if the treatment effect were zero (Mantel & Haenszel, 1959).[24] Rosenbaum (2002) shows that this test statistic can be bounded by two known distributions: if the $e^{\gamma} = 1$, there is no hidden bias. With increasing e^{γ}, however, the bounds move apart and there is less certainty about the estimated treatment effect due to unobserved selection bias (Becker and Caliendo, 2007).

The most likely threat to the robustness of the estimated ATTs is the possibility of a negative selection bias due to unobserved covariates that affect both pursuit of AMO studies and willingness to work in rural remote areas. In short, we are wary that those most likely to pursue an AMO education tend to be less willing to work in rural remote areas even without AMO education, and that the estimated negative effect is too large.

(Table 7 around here)

Table 7 exhibits the lower bounds of the Mantel-Haenszel statistic and the robustness of the effect of education on willingness to work in rural remote areas. Under the assumption that there is no bias caused by unobserved variables affecting the selection into the AMO group ($e^{\gamma}=\Gamma=1$)[25], there is a significant treatment effect. The existence of an omitted variable may lead to larger differences between the two groups' odds ratio of being in the AMO group; the gamma (Γ) will then increase. In that case, assuming there is a negative unobserved selection bias, the test statistic when there is no bias is too low, and is consequently adjusted upwards. In Table 7, the test statistic increases as Γ increases. The estimated treatment effect is significant at a 5% level until increasing gamma up to 65 percentage points. This means that the results are insensitive to an unobserved selection bias that would increase the odds of

[23] If, for example, $e^{\gamma} = 2$, two persons with the same propensity score can differ in the odds of being treated with a factor of up to two.
[24] The test is based on random sampling, so an important precondition is that the individuals be properly matched.
[25] This refers to the situation where $e^{\gamma}=1$.

pursuing AMO studies by close to 65%. The estimates thus seem to be robust to a relatively high degree, assuming we have underestimated the true treatment effect.

The sensitivity of estimates for overestimation was also checked; however, the effect becomes increasingly significant as we increase the assumed overestimation of the true treatment effect.

7. Concluding remarks

The average effect of becoming an AMO on preference to work in rural remote areas is negative and substantial both with simple regressions (ATE) and when the more sophisticated propensity score method is applied (ATT). Depending on the specifications and method, becoming an AMO decreases the probability of preferring a job in a rural remote area by between 12.9 and 20.1 percentage points. Consequently, again depending on the specification, AMOs have a predicted probability of preferring a job in a rural remote area of 15.9% and lower. Knowing that 21.5% of AMO students came from CO jobs in rural remote districts, this goes a long way in suggesting that a policy aimed at recruiting health personnel to rural remote areas by offering COs jobs that include possibilities of upgrading of their education after a certain period of service may be a temporary measure only. This picture squares well with the hypothesis discussed in section 2.2, where increased education leads to more job opportunities and increased mobility. Increased mobility is not in itself negative, but increased mobility among those health workers that were initially attracted to rural remote areas as COs would not seem to benefit the rural remote areas of Tanzania. The current situation, where the AMOs are relatively more unequally distributed between rural and urban districts than the COs are, is thus likely to be reinforced by implementation of such a policy. Still, if the goal of the policy makers is to ensure that there are health workers with basic clinical skills in rural remote areas at any point of time, offering additional education opportunities after a certain period of service may be reasonably successful. If the goal is to ensure first recruitment and then retention, this may not be the best policy.

A possible way around the problem of increased centralisation as result of allowing health workers to upgrade their clinical skills could be to offer upgrading opportunities on condition of a certain period of service after having become an AMO also. However, COs considering where to work would probably take such an extra service period into account when making a choice, and adjust their initial preference for the CO job in the rural remote area downwards. This could be an interesting avenue for further research. Moreover, this analysis is based on stated preferences; a follow up with revealed preferences or a randomised trial has the potential to give more strength to the present findings, or of course to contradict them.

Finally, the analysis in this paper suggests that there are available possibilities for policy makers intent on attracting health workers to rural remote districts beyond offering education opportunities. In our sample, only 33.1% of CO students and 27.1% of AMO students have a rural background, while the regressions show a high correlation between preference to work in a rural remote area and having a rural background. Hence, encouraging more students with links to rural remote areas to become health workers seems to be one such possibility.

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Tables

Table 1: Descriptive statistics before matching

		N	Mean	Median	SD	CV[a]	Skewness	Kurtosis
Total	Willingness to work in rural area	388	0.253***	0	0.435	1.722	1.139	2.297
CO (AMO=0)	Female	281	0.359	0	0.481	1.337	0.586	1.343
	Age	274	30.869	26	8.879	0.288	1.093	3.026
	Single	281	0.577	1	0.495	0.859	-0.310	1.096
	Dependents	281	0.488	0	0.501	1.027	0.050	1.002
	Parents living in rural remote area	281	0.331	0	0.471	1.424	0.718	1.516
	Ambitions to become an in-charge	281	0.890	1	0.314	0.353	-2.488	7.189
	Motivated by helping others	281	0.210	0	0.408	1.943	1.424	3.028
	Strong professional interest	281	0.338	0	0.474	1.402	0.685	1.469
	Willingness to work in rural area	281	0.288	0	0.454	1.574	0.935	1.874
AMO (AMO=1)	Female	107	0.346	0	0.478	1.382	0.648	1.420
	Age	104	38.048	37	6.330	0.166	0.286	2.220
	Single	107	0.159	0	0.367	2.312	1.866	4.483
	Dependents	107	0.972	1	0.166	0.171	-5.718	33.696
	Parents living in rural remote area	107	0.271	0	0.467	1.648	1.030	2.061
	Ambitions to become an in-charge	107	0.776	1	0.419	0.540	-1.322	2.747
	Motivated by helping others	107	0.234	0	0.425	1.820	1.259	2.585
	Strong professional interest	107	0.243	0	0.431	1.773	1.198	2.436
	Willingness to work in rural area	107	0.159	0	0.367	2.312	1.866	4.483
Difference[b] (CO - AMO)	Female		0.014	(0.250)				
	Age		-7.176***	(-8.117)				
	Single		0.418***	(7,365)				
	Dependents		-0.484***	(-8,779)				
	Parents living in rural remote area		0.060	(1.135)				
	Ambitions to become an in-charge		0.114***	(2.873)				
	Motivated by helping others		-0.024	(-0.505)				
	Strong professional interest		0.095*	(1.805)				
	Willingness to work in rural area		0.129***	(2.618)				

*** there is a significant difference between the two groups, $p < 0.01$
** there is a significant difference between the two groups, $p < 0.05$
[a] coefficient of variation (sd/mean)
[b] z-values from the two-sample Wilcoxon rank-sum test in parentheses

Table 2: Probit regressions of willingness to work in rural remote areas

	(1)	(2)	(3)
AMO (d)	-0.129***	-0.158***	-0.157***
	(0.044)	(0.044)	(0.044)
Female (d)		-0.019	-0.024
		(0.043)	(0.042)
Age		0.003	0.003
		(0.003)	(0.002)
Single (d)		-0.075	-0.075
		(0.056)	(0.055)
Dependents (d)		0.008	-0.003
		(0.056)	(0.056)
Parents living in rural remote area (d)		0.279***	0.271***
		(0.051)	(0.050)
Ambitions to become an in-charge (d)			-0.107*
			(0.056)
Very willing to help (d)			0.058
			(0.051)
Strong professional interest (d)			0.076*
			(0.046)
Predicted probability of preferring a job in a rural remote area	0.2526	0.2524	0.2514
Log likelihood	-215.609	-192.39182	-188.72034
Pseudo R^2	0.0167	0.1226	0.1394
N	388	388	388

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Base of the propensity score, probit regression

AMO	Coefficient
Female	0.058
	(0.167)
Single	-0.667***
	(0.196)
Dependents	1.750***
	(0.297)
Parents living in rural remote area	-0.307*
	(0.174)
Ambitions to become an in-charge	-0.408*
	e0.211)
Motivated of helping others	0.143
	(0.192)
Strong professional interest	-0.505***
	(0.181)
Constant	-1.218***
	(0.340)
Log likelihood	-165.10883
Pseudo R^2	0.2774
N	388

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Descriptive statistics, common support

		N	Mean	Median	SD	CV[a]	Skewness	Kurtosis
CO	Female	147	0.401	0	0.492	1.225	0.402	1.162
	Single	147	0.272	0	0.447	1.641	1.024	2.049
	Dependents	147	0.932	1	0.253	0.271	-3.431	12.773
	Parents living in rural remote area	147	0.381	0	0.487	1.279	0.490	1.240
	Ambitions to become an in-charge	147	0.871	1	0.337	0.387	-2.210	5.885
	Motivated by helping others	147	0.231	0	0.423	1.829	1.275	2.624
	Strong professional interest	147	0.374	0	0.486	1.298	0.520	1.271
	Willingness to work in rural area	147	0.347	0	0.448	1.377	0.634	1.414
AMO	Female	107	0.346	0	0.478	1.382	0.648	1.420
	Single	107	0.159	0	0.367	2.312	1.866	4.483
	Dependents	107	0.972	1	0.166	0.171	-5.718	33.696
	Parents living in rural remote area	107	0.271	0	0.447	1.648	1.030	2.061
	Ambitions to become an in-charge	107	0.776	1	0.419	0.540	-1.322	2.747
	Motivated by helping others	107	0.234	0	0.425	1.820	1.259	2.585
	Strong professional interest	107	0.243	0	0.431	1.773	1.198	2.436
	Willingness to work in rural area	107	0.159	0	0.367	2.312	1.866	4.483
Difference[b]	Female		0.055	(0.900)				
(CO - AMO)	Single		0.113**	(2.132)				
	Dependents		-0.040	(-1.425)				
	Parents living in rural remote		0.110*	(1.830)				
	Ambitions to become an in-charge		0.095**	(1.991)				
	Motivated by helping others		-0.003	(-0.044)				
	Strong professional interest		0.131**	(2.210)				
	Willingness to work in rural area		0.188***	(3.336)				

* p < 0.10, ** p < 0.05, *** p < 0.01
[a] coefficient of variation (sd/mean)
[b] z-values from the two-sample Wilcoxon rank-sum test in parentheses

Table 5: Normalised differences in means before and after matching

	Before matching	After matching
Female	-0.0201	-0.0810
Single	-0.6776	-0.1958
Dependents	0.9183	0.1323
Parents living in rural remote area	-0.0923	-0.1663
Ambitions to become an in-charge	-0.2177	-0.1768
Motivated by helping others	0.0402	0.0039
Strong professional interest	-0.0951	-0.2020

Note: all standardised differences after matching are well below the 0.25 level.

Table 6: ATT with different matching algorithms

Matching algorithm	No. treated	No. controls	ATT	Analytical st. error	Bootstrapped st. error
Nearest neighbour	107	118	-0,154***	0,065	0,068
NN within radius	107	147	-0,195***	0,057	0,058
Stratification	107	147	-0,201***	0,057	0,060
Kernel	107	147	-0,183***	-	0,058

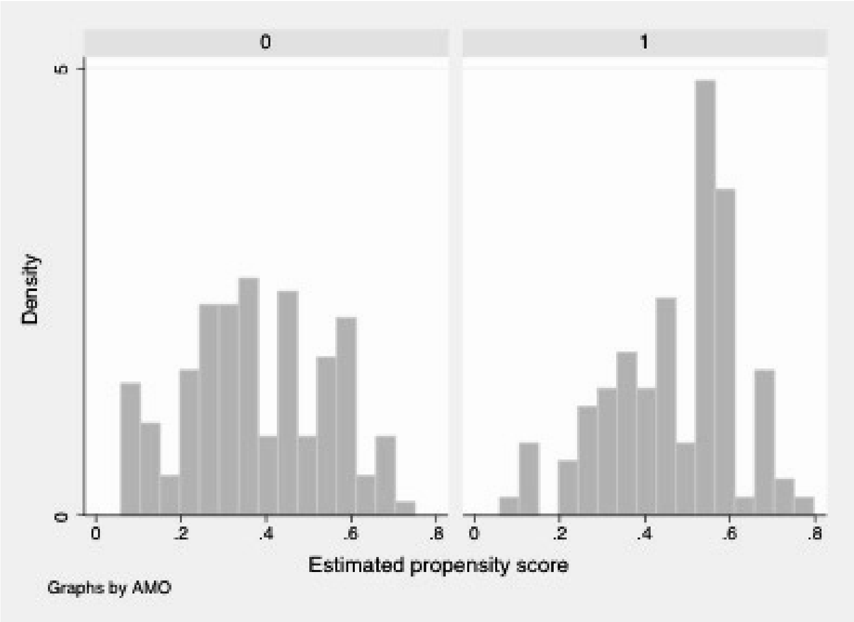
Table 7: Sensitivity to bias caused by omitted covariates

Gamma (Γ)	**Lower MH bound**	**Lower bound p-value**
1	3.220	0.000641
1.1	2.914	0.001784
1.2	2.625	0.004326
1.3	2.362	0.009087
1.4	2.120	0.017018
1.5	1.895	0.029033
1.6	1.686	0.045881
1.7	1.491	0.068033
1.8	1.307	0.095639
1.9	1.133	0.128516
2	0.969	0.166188

Note: The table shows the lower bounds of the Mantel-Haenszel statistic.

Figures

Figure 1: Propensity score in the common support region



Appendix

A. 1

List of schools in the sample and description of sampling procedure

CO Schools
Kibaha Clinical Officer Training Centre
Lindi Clinical Officer Training Centre
Lushoto Clinical Officer Training Centre
Machame Clinical Officer Training Centre
Mafinga Clinical Officer Training Centre
Masasi Clinical Officer Training Centre
Mtwara Clinical Officer Training Centre
Musoma Clinical Officer Training Centre
Mvumi Clinical Officer Training Centre
Sengerema Clinical Officer Training Centre

Selection procedure: Ten schools were drawn randomly from 18 clinical officer training centres. Two were excluded because of logistical problems (they were very remote and difficult to reach at the planned time for data collection, and had very few students), so two more schools were randomly drawn from the total sample. Note that CO training centres are obliged to recruit students from all over Tanzania and that there are no systematic differences between students or teaching programs, so the sample is likely to be representative even though two remote schools were excluded.

AMO Schools
Bugando Assistant Medical Officer School
KCMC Assistant Medical Officer School
Tanga Assistant Medical Officer School

Selection procedure: Three out of four schools that were in practice educating all the general AMOs in Tanzania were selected. These three schools were conveniently located on the planned route for data collection at the CO training centres. Note that AMO schools are obliged to recruit students from all over Tanzania and that there are no systematic differences between students or teaching programs, so the sample is likely to be representative even though one school was excluded.