Does Doing an Apprenticeship Pay Off? Evidence from Ghana*

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Abstract

In Ghana there is a highly developed apprenticeship system where young men and women undertake sector-specific private training, which yields skills used primarily in the informal sector. In this paper we use a 2006 urban based household survey with detailed questions on the background, training and earnings of workers in both wage and self-employment to ask whether apprenticeship pays off. We show that apprenticeship is by far the most important institution providing training and is undertaken primarily by those with junior high school or lower levels of education. The summary statistics indicate that those who have done an apprenticeship earn much less than those who have not. This suggests that endogenous selection into the apprenticeship system is important, and we take several measures to address this issue. We find a significant amount of heterogeneity in the returns to apprenticeship across education. Our most conservative estimates imply that for currently employed people, who did apprenticeships but have no formal education, the training increases their earnings by 50%. However this declines as education levels rise. We argue that our results are consistent with those who enter apprenticeship with no education having higher ability than those who enter with more education.

Keywords: Apprenticeship; Africa; Training; Treatment; Control function
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1 Introduction

Skills training in Ghana occurs in both the private and public sectors. By far the most important institution which provides such training in the private sector is the traditional apprenticeship system. Apprentices are young men and women who undertake highly sector-specific training. Some of these apprentices then go on to form their own businesses, others go on to work in the firm in which they were apprentices as masters/mistresses, some move to other firms or occupations. While much is known about the institution in terms of its structures and forms, we know much less about how well apprenticeship pays relative to other forms of training and relative to more academic education. Given the prevalence of apprenticeships, we believe that improving our knowledge about the returns to such training is very important. Moreover, in light of the rise in the importance of the informal sector in providing job opportunities in urban areas (Kingdon, Sandefur, & Teal, 2006), and the accompanying dominance of apprenticeship as the training option in this sector, the questions regarding the size of the returns to apprenticeship are all the more relevant.[1]

We attempt to fill the gap in the literature by focusing here explicitly on apprenticeships. We begin by speculating about the underlying dimensions of apprenticeship training, both economic and social. The economic consequences from doing an apprenticeship are twofold: apprenticeships raise one's potential earnings and also improve one's chances of having a job. In addition, apprenticeship is a social as well as an economic undertaking for many young Ghanaians. As apprentices, young people mature while developing job-oriented skills.

In this paper we focus exclusively on the effect of apprenticeships on earnings for those people who report an earned income. We abstract from the issue of labour market participation. Rather, we are choosing to compare two similar groups: income earners who have not invested in apprenticeship training and income earners who have. Therefore our research question is

[1]While we address questions specific to Ghanaian apprenticeship, the analysis links to the long history in Ghana, and elsewhere, of the relative value of academic relative to vocational education (Foster, 1965a, 1965b) and to the policy debate as to how public provision compares with the private provision of training (Middleton, Ziderman, & van Adams, 1993).

very specific: does apprenticeship pay for those who have earned income?

Measuring these economic returns to apprenticeship is a difficult undertaking for three reasons. First, the data requirements are quite important; as Frazer (2006) argues, apprenticeship is most commonly a form of skill acquisition which pays off in self-employment if the apprentice acquires sufficient capital to start their own business. Thus to establish the effect of apprenticeship it is essential to observe individuals in both the wage and self-employment sectors. We use data from the CSAE/GSO's Ghana Urban Panel Household Survey (GUPHS) that includes detailed information on training for individuals and measures the incomes of the self-employed with as much accuracy as possible in a manner that allows incomes to be compared across the formal and informal sectors.

Secondly, the endogeneity of education caused by omitted unobservables must be addressed. We use a control function approach (in the first stage) in order to have a flexible functional form in the earnings equation. In addition, we are interested in the interplay between education and apprenticeship and must explicitly allow for the potential importance of the returns to education being convex.

Finally, we deal with the endogeneity issues surrounding apprenticeship inherent in our non-experimental data. The main reason why endogeneity would be an issue is an omitted variables problem due to ability: people who are more able are more likely to earn a high return from apprenticeship and earn a high income. Alternatively it may be true that less able people choose apprenticeship over education more often than high ability people, or less able individuals have difficulty finding jobs and therefore go into an apprenticeship. We control for ability by including scores on skills tests and the score on the Raven's test. An additional source of endogeneity may be a specific "aptitude for apprenticing" which makes certain individuals benefit much more from this type of training than others. To address endogeneity caused by ability bias (that remains unobservable after the Raven's test) and this so-called aptitude bias, we also pursue an instrumenting strategy, using a treatment effects (IV) approach as well as a control function in the first stage. The control function offers the advantage over the IV that allows for heterogeneity across the education spectrum, which proves to be crucial here.

In the next section, we assess how important apprenticeship is as a form of training in order to motivate the need for this analysis. In Section 3 we describe the relationship between education and apprenticeship choices. Section 4 describes the data, and Section 5 discusses modeling issues. Section 6 presents the results and argues that the payoff from being an apprentice depends on the education level at which it is undertaken. In Section 7, we present an internal rate of return analysis. A final section concludes.

2 How important is apprenticeship as a form of training?

We begin by establishing the importance of apprenticeship in Ghana.[2] We draw on the 1984 and 2000 Ghanaian Censuses, the Ghana Living Standards Survey 4 (GLSS 4), and our own data to argue that apprenticeship is a key form of training. It is common among workers in all sectors but especially among urban workers in the informal sector.

Table 1: Manufacturing Employment in the Population Census

	1984		2000		Growth
	Empl.	Share	Empl.	Share	Rate
Wage Employees					
Public	27,172	4.6	34,275	4.3	1.5
Private	65,931	11.2	100,174	12.7	2.6
Apprentices	25,332	4.3	78,834	10.0	7.1
Other	18,684	3.2	15,873	2.0	-1.0
Total Employed	137,119	23.3	229,156	29.1	3.2
Self-Employed					
Without Employees	430,029	73.1	490,276	62.2	0.8
With Employees	21,270	3.6	68,636	8.7	7.3
Total Self-Employed	451,299	76.7	558,912	70.9	1.3
Total	588,418	100.0	788,068	100.0	1.8

Source: Author's calculations based on published statistics from the Ghana Statistical Service census reports (Ghana Statistical Service, 1984, 2005).

As Table 1 shows, there has been a marked increase in the absolute number of (current) appren-

[2]While there are several formal institutions that offer vocational training in Ghana, we focus here on traditional apprenticeships that take place in the enterprise itself.

tices across the manufacturing sector in Ghana, and their portion of wage employees has also risen substantially from 1984 to 2000. It is likely that much of the increase in the number of people trained in apprenticeships has been absorbed by small firms and the self-employed.

Table 2: Training among working age Ghanaians, 1998-99, GLSS 4

	Urban		Rural		All	
	No.	Share	No.	Share	No.	Share
Total Sample						
Current Apprentices	364	2.7	380	2.8	744	5.6
Past Apprentices	1,008	7.5	1,473	11.0	2,481	18.5
No Apprentice Training	3,472	25.9	6,706	50.0	10,178	75.9
Total	4,844	36.1	8,559	66.4	13,403	100.0

Source: Author's calculations based on the GLSS 4. Sample excludes those under age 15 and over age 65 and those who did not report apprenticeship status.

Table 2 shows summary statistics for the working age population—all people between ages 15 and 65, whether in or out of the labour force—from the GLSS 4. Apprentices make up nearly 25% of working-age Ghanaians and 28% of urban residents, assuming the GLSS is a nationally representative sample; this figure is even higher for the employed (figures not reported).

Table 3: Training and Apprentices in Ghana, 2006, GUPHS

	No.	Share
Apprentices		
No Formal Training	1,078	65.6
Current Apprentices	122	7.4
Past Apprentices	317	19.3
Any Other Vocational/Technical Training	126	7.7
Total	1,643	100.0
Training Events		
Current Apprentices	122	15.4
Past Apprentices	317	40.1
Current vocational trainees	16	2.0
Past vocational trainees	112	14.2
Current on-the-job trainees	40	5.1
Past on-the-job trainees	158	20.0
Trained teacher/nurse	25	3.2
Total number of training events	790	100.0

Source: Author's calculations based on the GUPHS. Total number of training events does not account for double counting, e.g. one person with vocational and apprenticeship training counts as two events.

Within our sample of people aged from 15 to 65 from the GUPHS, including those both in and outside the labour force, 26.7% have done some form of training as an apprentice (see Table 3).[3] In Table 3 we also identify both current and past training events of all types (vocational/technical, apprenticeship, on-the-job and teacher/nursing) in order to demonstrate that apprenticeship is by far the most common.[4] Current apprenticeships account for 15% of the training events in the survey while past apprenticeships comprise 40%. The second most important form of training is that classified as on-the-job, followed by vocational training, excluding that for teachers and nurses, who constitute 3% of the training events.

2.1 Shortage of literature

We believe that we have now established the importance of apprenticeship as a form of skills training in Ghana. Yet there is a dearth of research on this topic. Most studies investigate the private and social returns to formal training in developing countries but there are few papers on apprenticeships specifically (as indicated in the literature review by Middleton et al. (1993)). Rosholm, Nielsen, and Dabalen (2007) find a 20% wage increase due to formal training in Kenya and Zambia. However, they focus only on training undertaken at formal vocational and technical institutions; apprenticeships are mentioned only briefly and are not explicitly studied. Using data from Ghana, Jones (2001) finds a statistically significant, large positive return to vocational training for wage earners when it is differentiated from formal education. Jones (2001) does not highlight this result in her paper, but the coefficient in her earnings equation is roughly .5, which, assuming her vocational variable is a dummy variable, would imply that workers with formal vocational training earn 65% more than those who do not, on average.

As for apprenticeships, Grootaert (1988) finds a small and insignificant return to years of apprenticeship for urban residents and 17% increase in annual earnings from a year of appren-

[3]This figure includes people who have also undertaken teaching and nursing training.

[4]Many individuals do more than one form of training. The "training events" in Table 3 do not correct for double counting.

ticeship for rural residents in Côte d'Ivoire, though apprenticeship is not treated as endogenous in the earnings equation. Mabawonku (1979), in contrast, found very high rates of return for apprenticeships in northern Nigeria. In a more recent paper, Frazer (2006) uses Ghanaian Manufacturing Enterprise Survey (GMES) and GLSS 4 data from the 1990s and presents earnings equations in which the return to apprenticeship is very low on average, though he assumes apprenticeship is exogenous. He finds with the GLSS 4 that wages rise by about 7% for those with apprenticeship training in his sample that includes all workers; wage earners earn only slightly more after doing an apprenticeship, though this is insignificant. However the return for the self-employed, who benefit most from apprenticeship in Frazer's model, is much higher at 19% and is statistically significant. He also finds in the GMES data that wage employees in the manufacturing sector actually earn less if they have done apprenticeships.

In assessing the returns to apprenticeships this literature currently has two limitations. First, nearly all of these papers look at the wage returns to training undertaken by those in wage employment. By measuring self-employment in a manner comparable to wage earners, our data (the 2006 GUPHS)allow us to assess the return in a more comprehensive and believable way. Second, there is a distinct lack of research treating the econometric issues of endogeneity of the apprenticeship decision. Our paper addresses both of these concerns.

3 Educational background and occupational outcomes of the apprentices

In Table 4 we present the educational background of the individuals in the sample and for apprentices in order to asses how their educational patterns differ. Table 5 presents a similar breakdown for occupational outcomes.

It is clear from Table 4 that by far the most common pattern for apprentices is to enter training after the end of junior high school, which under the old education system was the end of middle school. Of those individuals in the sample who had done an apprenticeship in the past, 74% entered at the junior high school level. However, it will prove to be of importance for the results

Table 4: Educational Background, 2006

	No.	Share
Total Sample		
No education (years<6)	226	13.7
Primary (years between 6 and 9)	218	13.3
Middle/JSS (years 9 or 10)	896	54.5
Secondary	283	17.2
Post-Secondary	13	0.8
Polytechnic	7	0.4
Total	1,643	100.0
Past Apprentices		
No education (years<6)	29	9.1
Primary (years between 6 and 9)	32	10.1
Middle/JSS (years 9 or 10)	233	73.5
Secondary	23	7.3
Post-Secondary	0	
Polytechnic	0	
Total	317	100.0

Source: Author's calculations based on the GUPHS.

Table 5: Occupational Outcomes, 2006

	No.	Share
Total Sample		
Self-Employed	549	33.4
Small Firm (<10 employees)	272	16.6
Large Firm ($\geq$10 employees)	197	12.0
Public Sector	64	3.9
No Earned Income	561	34.1
Total	1,643	100.0
Past Apprentices		
Self-Employed	181	57.1
Small Firm (<10 employees)	54	17.0
Large Firm ($\geq$10 employees)	30	9.5
Public Sector	8	2.5
No Earned Income	44	13.9
Total	317	100.0

Source: Author's calculations based on the GUPHS. Current apprentices are considered wage employees even if their earned income is zero.

below to note that while this pattern is by far the most common, there are different paths through formal education and apprenticeship; for instance, some 9% of those who have done an apprenticeship have no education. A comparison of the educational background of those who did an apprenticeship with the whole sample shows that it is those with junior secondary or below who are more likely to be apprentices than those with higher levels of education. Indeed there is nobody in the sample who undertook an apprenticeship who completed a post secondary qualification.

Table 5 shows that the most common pattern for apprentices is to be self-employed. Many of them also work in small firms (as defined as firms with fewer than 10 employees). This is further evidence that the role of apprenticeship in urban settings is very particularly important for informal sector jobs.

4 Measuring incomes for the self-employed

In order to answer the question does apprenticeship pay it is clearly crucial to be able to measure self-employment income. Our data are taken from a longitudinal labor market survey conducted by the Centre for the Study of African Economies (CSAE) at Oxford University, under the direction of the authors and in collaboration with the Ghana Statistical Office (GSO). The urban panel survey collects information on incomes, education and labor market experience, household characteristics and various other modules for labour force participants (ages 15 to 65) in urban areas. For Ghana these areas span the four largest urban centers in the country: Accra (and neighboring Tema), Kumasi, Takoradi and Cape Coast. The samples were based on a stratified random sample of urban households from the 2000 census in Ghana.[5] While the initial sample was household based, interviews were conducted on an individual basis, and the unit of analysis in what follows will be at the individual level.

Collecting income data on the self-employed in low-income countries is a controversial endeavor. Field guides for the World Bank's Living Standards Measurement Surveys (LSMS), which serve as the international standard for household surveys in development economics, recommend

[5]We should note that the analysis in this paper does not incorporate data from the Ghana Manufacturing Enterprise Survey (GMES). The GUPHS and the GMES are conducted in parallel with a common survey instrument. However, we restrict ourselves in this paper to the population based sample of the GUPHS, excluding the firm-based sample of manufacturing employees interviewed through the GMES. A total of 830 were interviewed in the first round of the survey in Ghana, which was conducted between October 2003 and June 2004.

survey managers not collect this information. The stated rationale is that self-employed business people in the informal sector rarely keep written accounts and their self-reported income data may be too noisy to be of use. For household based enterprises, the distinction between business and personal expenditures may be completely alien to respondents. We acknowledge the validity of these concerns.

However, because the non-agricultural self-employed constitute a majority of the urban working population in Ghana, we feel measuring such incomes is essential to our current objective of understanding the impact of apprenticeship on welfare. Our income measure for the self-employed is based on self-reported profits. Profits are net of routine operating expenses and gross of fixed capital expenditure, if any. The concepts of "revenue", "business costs", and "profits" are explained to respondents by enumerators with experience in conducting firm and household surveys. As the surveys are entered directly onto handheld computers, a simple mechanical check forces enumerators to go over the numbers again if revenue, cost and profit figures are inconsistent. Enumerators have reported few conceptual difficulties with this portion of the questionnaire.[6]

5 Modeling the effects of training

Because apprenticeship is a binary variable, there are several approaches that we use to model its impact on earnings. Our estimation strategy broadly follows two methods. In one approach, we draw on the program evaluation literature and estimate the treatment effect of apprenticeship training using IV. We estimate the results under various assumptions. We also attempt to improve on the efficiency of the estimators where possible. In a second method, we use a control function in the first stage, essentially treating apprenticeship as a simple endogenous regressor like any other. Both methods rely on the same set of instruments (discussed in Section

[6] In the results in Section 6, we do not "trim the sample" to account for possible misreporting of earnings. However, we did rerun the regressions without the bottom 1% and top 1% of income earners, and the results were unchanged.

5.3).[7]

5.1 Treatment effects

Let's start with the treatment effects approach.[8] Let a be the binary treatment indicator (where $a = 1$ denotes treatment and $a = 0$ otherwise), and the outcome of interest is defined as y_0 without treatment and y_1 with treatment. In our analysis, a is apprenticeship, and the outcome of interest is earnings. The standard problem is that we do not observe the counterfactual, i.e. what earnings would be for the apprentice had he/she not done the apprenticeship. The average treatment effect (ATE) is defined as:

$$ATE = \mathrm{E}(y_1 - y_0)$$

The average treatment effect on the treated (ATT) is then:

$$ATT = \mathrm{E}(y_1 - y_0|a = 1)$$

In this paper, we are most interested in determining ATT, as we want to find out how apprenticeship has affected earnings for those people who have actually done it. The observed outcome y can be expressed as:

$$y = y_0 + a(y_1 - y_0)$$

If we express y_0 and y_1 as the sum of their means and stochastic parts:

$$y_1 = \mu_1 - v_1, \mathrm{E}(v_1) = 0 \tag{1}$$

$$y_0 = \mu_0 - v_0, \mathrm{E}(v_0) = 0 \tag{2}$$

it is then helpful to express y as a switching model:

$$y = \mu_0 + (\mu_1 - \mu_0)a + v_0 + a(v_1 - v_0) \tag{3}$$

[7] As discussed in Section 3, the link between education and the returns to apprenticeship are crucial in this analysis. As will become clear below, the problem of a common support meant that we did not pursue a propensity score matching analysis of the data and instead chose a more flexible framework.

[8] Note that this section relies heavily on the exposition in Chapter 18 of Wooldridge (2002), as well as Fafchamps (2006).

The ATE (unconditional on $\mathbf{x}$) is then the coefficient on a, and the last term allows for an individual-specific effect of a. Estimating Equation 3 by OLS yields inconsistent estimates because typically a is correlated with the error term, i.e. participation in training is correlated with some unobserved characteristic(s). However, if $v_0 = v_1$, which implies that ATE=ATT, and a is randomly assigned, then OLS estimates are consistent because the last term disappears. Alternatively, assuming that y_0 and y_1 are mean independent of a as opposed to $v_0 = v_1$ would also produce consistent OLS estimates because $\mathrm{E}(v_1 - v_0|\mathbf{x}, a) = \mathrm{E}(v_1 - v_0|\mathbf{x}) = 0$.

5.1.1 Homogeneous treatment

In this paper, we start by adopting the assumption that the stochastic (unobservable) elements of y_0 and y_1 are equal: $v_0 = v_1$. This is also known as the common treatment effect assumption (because it implies $ATE = ATT$). It does not allow for size of the treatment effect to vary over different values of $\mathbf{x}$, and it explicitly imposes homogeneous treatment effects across individuals. It implies that everyone benefits in the same way from the treatment. We can then write down the following simple Mincerian wage model (Mincer, 1974):

$$\text{Models 1a, 1b:} \quad \ln(wage)_i = \gamma + \alpha a_i + \mathbf{x}_i\beta_0 + u_{0i} \tag{4}$$

where a_i is a dummy variable that takes the value of 1 if the person has completed an apprenticeship and zero otherwise, and $\mathbf{x}_i$ is an vector of individual characteristics. We are interested in finding out the value of α, the ATE. Although we do not have the interaction term from Equation 3 to worry about, we still want consider the possibility that a and u_0 may be correlated. If we believe a to be endogenous, then this regression can be estimated by IV, instrumenting the endogenous binary variable with instruments $\mathbf{z}$ (Wooldridge, 2002). This is also called the dummy endogenous variable model (Heckman, 1978). We will refer to this method as Model 1a. Although $v_0 = v_1$, we do not need the additional assumption of conditional mean independence of the treatment a and v_0 and v_1 (conditioned on $\mathbf{x}$). This is because the interaction term in Equation 3 will disappear (and hence no interaction term is included in Equation 4). Conditional mean independence is replaced with the standard IV assumptions that a vector $\mathbf{z}$

of instruments is available. Thus the three assumptions necessary for Model 1a are: $v_0 = v_1$; $\mathrm{L}(v_0|\mathbf{x},\mathbf{z}) = \mathrm{L}(v_0|x)$; and $\mathrm{L}(a|\mathbf{x},\mathbf{z}) \neq \mathrm{L}(a|\mathbf{z})$ (where L is the linear projection).

To improve on the efficiency of the simple IV estimator from Model 1a when the endogenous variable is binary, one can adopt slightly stronger assumptions: $v_0 = v_1$; $\mathrm{E}(v_0|\mathbf{x},\mathbf{z}) = \mathrm{L}(v_0|x)$ or the expectation of v_0 is linear in $\mathbf{x}$; $\mathrm{P}(a = 1|a,\mathbf{x}) = G(\mathbf{x},\mathbf{z})$ is of known parametric form; and $Var(v_0|\mathbf{x},\mathbf{z}) = \sigma_0^2$ (homoskedasticity). Effectively, we alter Model 1a to estimate a probit model in the first stage $\mathrm{P}(a = 1|a,\mathbf{x}) = G(\mathbf{x},\mathbf{z})$ by maximum likelihood, here regressing apprenticeship on $\mathbf{x}$ and $\mathbf{z}$, and then using the predicted values $\hat{G}_i$ (the propensity score) from this probit as the instrument in the second stage. We will refer to this as Model 1b.

5.1.2 Heterogeneous treatment

In Models 1a and 1b, we have assumed that $v_0 = v_1$. However, it is more interesting to consider the possibility that ATE and ATT may not be equal across individuals and that treatment effects may be heterogeneous. Indeed, we can allow for an individual specific effect, such that $v_0 \neq v_1$ by specifying a functional form for v_0 and v_1:

$$v_1 = g_1(\mathbf{x}) - e_1$$

$$v_0 = g_0(\mathbf{x}) - e_0$$

Here, we must assume conditional mean independence: $\mathrm{E}(y_0|\mathbf{x},a) = \mathrm{E}(y_0|\mathbf{x})$ and $\mathrm{E}(y_1|\mathbf{x},a) = \mathrm{E}(y_1|\mathbf{x})$. If we also assume that $g_1(\mathbf{x})$ and $g_0(\mathbf{x})$ are linear functions and that $\mathrm{E}(v_0) = \mathrm{E}(v_1) = 0$, then our equation that we would like to estimate becomes a heterogeneous treatment effects model with an interaction term allowing for the treatment effect to vary over values of $\mathbf{x}$:

$$\text{Models 2a, 2b, 2c:} \quad \ln(wage)_i = \gamma + \alpha a_i + \mathbf{x}_i\beta_0 + [a_i(\mathbf{x}_i - \bar{\mathbf{x}})]\delta + error_i \tag{5}$$

It follows that consistent estimators of ATE and ATT are:

$$\widehat{ATE} = \hat{\alpha}$$

$$\widehat{ATE}(\mathbf{x}) = \hat{\alpha} + ((\mathbf{x_i} - \bar{\mathbf{x}})\hat{\delta})$$

$$\widehat{ATT}(\mathbf{x}) = \hat{\alpha} + \left(\sum_{i=1}^{N} a_i\right)^{-1} \left[\sum_{i=1}^{N} a_i(\mathbf{x}_i - \bar{\mathbf{x}})\hat{\delta}\right]$$

where $\widehat{ATT}$ is essentially the $\widehat{ATE}$ weighted (conditioned) by participation. We can estimate this regression by OLS, which we call Model 2a. If we drop the assumption $\mathrm{E}(v_1) = \mathrm{E}(v_0) = 0$ and replace it with $\mathrm{E}(v_1|\mathbf{x}, \mathbf{z}) = \mathrm{E}(v_1|\mathbf{x})$ and $\mathrm{E}(v_0|\mathbf{x}, \mathbf{z}) = \mathrm{E}(v_0|\mathbf{x})$, then we must also assume $e_0 = e_1$ in order to have consistent estimates.

Keeping the linear form of $g_1(\mathbf{x})$ and $g_0(\mathbf{x})$, then we can use IV to estimate Equation 5. The IV estimator with the interaction terms is still consistent. We can proceed with instrumenting in two ways. First, we use the interaction of $\mathbf{z}$ with the demeaned covariates as instruments (in addition to $\mathbf{z}$). We call this Model 2b. Alternatively, we estimate the same probit $\mathrm{P}(a = 1|a, \mathbf{x}) = G(\mathbf{x}, \mathbf{z})$ in the first stage and find the predicted values. We use the predicted values, as well as the predicted values interacted with the chosen demeaned covariates, as the instruments in the second stage (Model 2c). This method is more efficient than Model 2b if we (again) assume homoskedasticity of v_0.

We are interested in heterogeneous treatment effects because it is quite possible that the return to apprenticeship may vary along the education and/or experience spectrums. Indeed, we will see later in the paper that the effect of apprenticeship on earnings is highly dependent on the level of education that one has attained. Allowing for the interaction then between apprenticeship and (demeaned) education as in Models 2a, 2b, and 2c will prove to be extremely important.

5.2 Control function

Finally, another approach outside of the treatment effects literature is the control function which calls for a basic 2SLS. We estimate a first stage linear probability model by regressing apprenticeship on the exogenous regressors and the instruments, while also controlling for city fixed effects. Because this involves a generated regressor, standard errors must then be bootstrapped in the second stage. It is worth nothing that this procedure is very similar to Model 1b, but we are simply using the residuals from our estimation of G as a regressor in the earnings equation, and G is estimated by OLS. Although this approach makes the strong assumption that we have correctly specified the parametric form for G, it potentially allows for more flexibility in the functional form used for earnings. Indeed, we are able to introduce an interaction term—apprenticeship interacted with demeaned education—into the modeling process in order to compare the control function results with the results from Section 5.1.2. In addition, we use a linear probability model in the first stage regression to simplify the correction (bootstrapping) of the standard errors in the second stage.

5.3 Can we identify the effects of apprenticeship?

In this paper, we are concerned with two sources of endogeneity. The first is the standard problem of the endogeneity of education, due to its correlation with unobserved elements in the error term that simultaneously affect earnings and therefore bias the OLS results. The second is the endogeneity associated with apprenticeship training.

5.3.1 Education

The labour economics literature on estimating the returns to education in the face of the endogeneity of education is extensive (see Card (2001) for a detailed discussion). In this paper we adopt a control function approach, which allows greater flexibility than the standard IV. This is crucial because of the convex nature of the returns to education, leading us to include a squared education term in our specification. Education is instrumented with household background variables that are correlated with the unobservables but not directly causally related to earnings (or variable of interest): closest brother's education (years) and closest sister's education (years). Those people without a brother and/or sister (a very small number, less than 1% of our estimation sample) or a missing value are assigned the mean.[9] These instruments are variables which are plausibly correlated (ideally strongly) with one's own education, as they reveal something about parental preferences for education as well as family background and common

[9] We also experimented with dropping them and giving those without siblings a value of zero; these changes do not affect the results in a significant way.

familial characteristics, but should have no relevant impact on one's current earnings.

Other possibilities for instruments that we considered were mother's education, father's education, distance from primary school, and distance from secondary school. Although these variables seem like good candidates *a priori*, they did not pass the overidentification tests and were thus invalidated. Therefore we did not include them in our first stage control function.

5.3.2 Apprenticeship

There are two sources of endogeneity of apprenticeship. The first is an omitted variables problem due to general ability, e.g. intelligence. Omitted ability will bias OLS estimates of the return to apprenticeship upward if high ability individuals are more likely to do an apprenticeship. If, on the other hand, it is the less able who cannot find a job or perform poorly in school who do an apprenticeship, then the bias might be downward. The second source of endogeneity may be unobserved "aptitude for apprenticing", i.e. those who enter apprenticeships have unobserved aptitude for such training and therefore experience higher returns than others would. This is a standard selection story that would cause the OLS estimates to be biased upwards. Given these potential directions of bias, we have no priors as to the overall sign of the bias in the OLS.

We partly address the issue of unobserved ability by controlling directly for ability in the earnings equation. We use several unique measures of ability which are usually unobserved to the econometrician in other datasets. The GUPHS included four comprehensive skills tests: mathematics, English and reading. In addition, a Raven's test was administered to all the individuals. This test aims to measure innate ability, ideally unrelated to academic learning. Implementing individual scores on these tests as dependent variables in our earnings regression should attenuate the omitted ability problem.

However, we are not convinced that the Raven's test is capturing all of what constitutes ability. Moreover, the problem of unobserved aptitude for apprenticing is also a concern. There is a distinct possibility that there are other unobserved attributes that drive selection into apprenticeship. Therefore we choose instruments that address this problem of unobservables. We aim to capture the decision to do apprenticeships by measuring access to an apprenticeship network and access to outside capital. These concepts form the basis of our instrument choices.

The first instrument we use reflects familial apprenticeship networking. We determine the number of other household members who have also done an apprenticeship. This is admittedly a rather crude and inexact measure, as it is not taken from the household roster but is rather dependent on whom in the household was interviewed at the individual level; however, it is presumably still correlated with the true value.

We are also interested in assessing access to credit. The convexity of the returns to formal education in Ghana imply that the best outcome by far for a child is to stay in formal education through university. In part these returns are due to the access to lucrative public sector jobs that comes with a university degree. For families who cannot afford the long-term investment in education the apprenticeship system offers an access to private sector training, though they are typically viewed as a last resort by parents—it is not viewed as a particularly desired outcome (Haan & Serriere, 2002). However apprenticeships may require a fee, and there is certainly an opportunity cost to doing them, so access to credit or savings matter for the decision to undertake this investment.

Therefore we choose two additional instruments that have a bearing on an individual's access to capital: a dummy for household access to credit, which takes the value of one if anyone in the household reported borrowing money from any source in the past year and zero otherwise; and a dummy for having internal, piped water in the house as a wealth indicator. Those with missing values for these three instruments are given the value of zero (the median and mode value of each); borrowing is relatively rare, so we felt it would be distortionary to replace missing values with the mean value. We had a choice to drop these observations but chose to keep the sample size as large as possible. We also considered using a third instrument—the amount (in cedis) others had borrowed in the household—but it was a weak instrument and tests indicated that it was redundant. Excluding it from the instrument set raised the precision of our estimates without affecting the point estimates in our final results.[10]

In addition, we make an explicit effort to ensure that these instruments (or at least a subset of them) identify apprenticeship separately from education—the concern is that access to capital influences formal education choices as well as apprenticeship. This concern does prove somewhat important when we regress education on its own instruments as well as the instruments for apprenticeship (results included in Appendix A, Table 13). However, the household's access to credit dummy is insignificant. This variable, then, is the most important for our identification strategy. If our instruments are successful in identifying participation in the apprenticeship system, then we should be able to find the causal effect of this training on earnings, conditional on observable individual characteristics.

6 Does being an apprentice pay?

6.1 Returns to apprenticeship

In Table 6 we report the descriptive statistics on which our analysis will be based. The sample is narrowed down to positive income earners. It excludes students, children under 18[11], adults over 65 and current apprentices. We assume that the individuals who did not complete the skills tests were unable to do so and therefore received zeros (this is a small proportion of the sample and does not change the results for the skills substantively). Observations with missing values for other relevant variables are dropped. Overall we are left with 931 individuals with an earned income.

The portion of apprentices in the sample is just under 29%. This reflects the fact that apprentices are relatively more successful in finding a job and are therefore more likely to be employed than others who have not done apprenticeships. Table 6 also suggests that there is an important

[10] The contemporaneous nature of our instruments could be a possible criticism of this approach. Since the GUHPS is part of a panel, it would be possible to look for lagged values of these instruments, although ideally we would need to know the values of such variables at the time when the apprenticeship started. We did not pursue this possibility because this would have narrowed down our sample size. We leave this avenue open for future research.

[11] We did not include 15 to 18 year olds, even though some of them may be working, because as we are excluding students, this would impose artificial selectivity onto the sample.

Table 6: Summary Statistics

$N = 931$	Past Apprentices Mean	Past Apprentices St. Dev.	Non-apprentices Mean	Non-apprentices St. Dev.
Male (=1 if male)	0.48	(0.50)	0.43	(0.50)
Age (years)	34.1	(9.5)	36.1	(10.8)
Raven's Score (out of 20)	4.13	(4.48)	4.73	(4.96)
Education (years)	8.56	(2.83)	8.08	(4.39)
Experience (years)	16.7	(9.6)	21.9	(12.4)
Monthly earnings (in 2006 cedis)	750,597	(604,817)	929,207	(945,326)
Ln(monthly earnings)	11.15	(0.86)	11.26	(0.99)
N	268		663	

Median earnings by education and gender	Past Apprentices	Non-apprentices
No academic education ($N = 136$):		
Monthly earnings	800,000	480,000
Monthly earnings if female	686,000	420,000
Monthly earnings if male	1,600,000	500,000
Any academic education ($N = 795$):		
Monthly earnings	600,000	700,000
Monthly earnings if female	400,000	500,000
Monthly earnings if male	800,000	800,000

Source: Author's calculations based on the 2006 GUPHS. Experience is labour market experience, defined as (Age - Education - Training time - 6). Training time is self-reported time (in years) spent in vocational training and/or apprenticeship. Earnings for the self-employed are based on self-reported profits.

distinction in terms of earnings profiles between those who do apprenticeships after receiving no formal education and those who do so after going to school.[12] This divergence in earnings for apprentices across the education spectrum, noted in Section 5.3, will prove important in the regression analysis.

Table 7 presents the second stage earnings equations. Earnings here are defined as monthly earnings in 2006 cedis. All the regressions include controls for additional skills tests and regional dummies, whose coefficients are not reported here. We excluded other determinants of earnings, such as occupation, because these are very likely to be determined in part by apprenticeship. Columns [1], [2] and [3] present three basic earnings functions to establish a basis for how the

[12] This distinction is a key reason why propensity score matching methods were difficult to use with these data. First, a common support is difficult to achieve because it is very rare for people in higher education to pursue apprenticeships. Second, the common support that can be established by comparing those with similar education levels presents problems with too few observations. Third, we would like to model the relationship between the return to apprenticeship and the level of education explicitly using an interaction term; this would not be possible with propensity score matching.

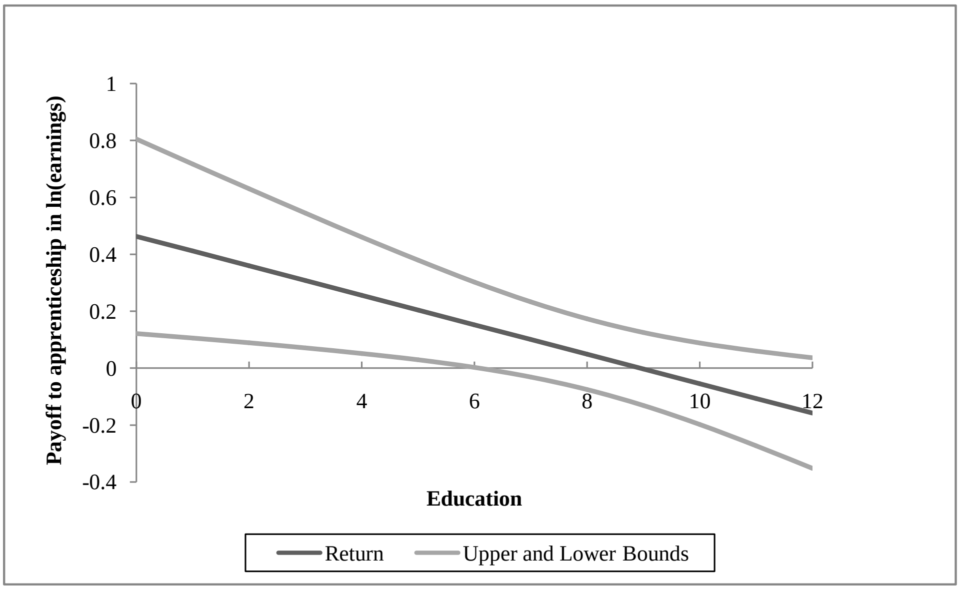
effects of apprenticeship may impact on earnings. We do not address any endogeneity problems in these columns. The first important thing to notice is that, without any controls, those with apprenticeship training earn on average less than other workers without apprenticeship training (Column [1]). This result clearly suggests selection into apprenticeship is an issue; no one would undertake costly privately funded training that offered no or negative return, and as we have already shown it is by far the most common form of training in Ghana.

In Column [2] we only control for gender, experience, hours worked and education, in Column [3] we include our control for reasoning ability, the Raven's score, as well as other skills (numeracy, English and reading—these three coefficients are not reported and are statistically insignificant). While this measure of ability decreases the return to education a little the impact is not large. This is consistent with a very wide range of evidence that any positive upwards bias on the OLS estimates of the return to education through any correlation between ability and education are small (see Card (2001) for a review). This ability variable does seem to suggest that the coefficient for apprenticeship in Column [2] is biased downwards due to ability, as the same coefficient is now positive in Column [3]. It may be because relatively low ability people do apprenticeships as an alternative to education. So, by controlling for ability, we find a positive, though insignificant and small, return to apprenticeship.

In Columns [4] through [9] in Table 7, we introduce a term "Educ control", which is the predicted residuals from a first stage control function for education (this methodology then requires bootstrapping of the standard errors because we have a generated regressor, which we do to 1000 repetitions). First stage results can be found in the Appendix. In Column [5], we follow the reasoning behind Model 2a and interact apprenticeship with (demeaned) education.[13] The ATE is then equal to .037, which means that apprenticeship has a small but very reasonable return of 3.8% ($= e^{.037} - 1$). We can also consider how this return changes across years of education. For example, for people with no years of education, earnings rise by

[13] We also tested other specifications in which we included several other demeaned interaction terms, but they were individually and jointly insignificant, so we were able to narrow it down to just the interaction term with demeaned education.

Figure 1: Returns to Apprenticeship, based on Table 7 Model 2a.



just under 59% ($= e^{(.037-.052*(-8.22))} - 1$) due to apprenticeship. This result is very precisely identified.[14] The effect of apprenticeship on earnings depends on when on the education path the apprenticeship is undertaken. A graph of the ATE and its confidence intervals can be seen in Figure 1.[15] The return is statistically different from zero below six years of education, but the confidence intervals do not allow us to reject the hypothesis of a positive return at the end of secondary school. The ATT, which is the ATE weighted by participation, in Column [5] is .02 for apprentices with the mean education level and .407 for those with no education. This implies that former apprentices with no education increased their earnings by 50% by doing the apprenticeship.

However, we have yet to control for any remaining endogeneity of participation in apprenticeship that is not captured by the Raven's score variable. This is presented in Columns [6] through [10] in Table 7. Columns [6], [7], [8], and [9] use Model 1a, Model 1b, Model 2b, and Model 2c, respectively. Columns [8] and [9] allow for the treatment effect to vary across levels of education, which Model 2a implies is non-ignorable. First stage results are included in the Appendix. The

[14] A linear combination of these two coefficients, evaluated for zero years of education (mean education is 8.22) and using robust but not bootstrapped standard errors, gives a coefficient of .461 with a t-stat of 2.66 and a confidence interval of .121 to .802, clearly different from zero.

[15] The confidence intervals for this graph are based on robust and not bootstrapped standard errors. This technicality makes little difference to the graph's message or appearance.

striking feature is that once we instrument for apprenticeship, the returns to this training rise significantly, and the coefficient on the interaction term becomes positive. The precision of the IV estimates is not as high as one would hope; this may be because the IV specification is too rigid to capture non-linearities across the education spectrum.

Column [10] offers a more flexible control function approach, where the first stage for apprenticeship is run as a linear probability model. "App Control" refers to the predicted residuals from this first stage (the results of the first stage are in the Appendix). Here again, as in Columns [8] and [9], the coefficient on the apprenticeship dummy is much higher than in Column [5]. This indicates that we may be correct in thinking that there are additional unobservable characteristics that bias the OLS results downwards. Specifically, general ability of the average apprentice could be quite low and thus pushes down the observed return. This result also provides rather strong evidence that an upward bias of the OLS induced by aptitude for apprenticing is not present—otherwise the point estimate in Column [10] would be closer to if not lower than Column [5]. However, we are not able to estimate the return very precisely as our standard errors remain too high.

Here the ATT equals .484, so apprenticeship raises earnings by about 62% ($= e^{.484} - 1$) for those who did the training (ceteris paribus). For those with no education, their income is more than doubled by the training ($1.37 = e^{.864} - 1$). This is a substantial gain and suggests that apprenticeship for those without education is a reasonable substitute for primary school. For those with 9 or 10 years of education, the ATT is .460, which translates to a 58% increase in earnings due to the training.[16]

[16]The results are not particularly sensitive to using a subset of the instruments. For example, if we run the model in Column [10] of Table 7 with any subset of the three instruments, the coefficient on the apprenticeship dummy varies from .409 to .758 but is never significant; the coefficient on the App x (Ed - $\bar{\text{Ed}}$) term is always -.051 and significant at the 5% level.

Table 7: **Full sample - dependent variable: ln(earnings)**

					Model 2a	Model 1a	Model 1b	Model 2b	Model 2c	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln(hrs worked per week)		.186	.166	.168	.177	.172	.172	.166	.170	.183
		(.064)***	(.065)**	(.066)**	(.066)***	(.071)**	(.070)**	(.082)**	(.071)**	(.063)***
Male		.429	.381	.362	.363	.346	.347	.346	.347	.340
		(.058)***	(.059)***	(.065)***	(.066)***	(.070)***	(.069)***	(.076)***	(.068)***	(.068)***
Experience (years)		.028	.031	.028	.027	.032	.032	.032	.032	.029
		(.010)***	(.010)***	(.011)**	(.011)**	(.012)***	(.012)***	(.014)**	(.012)***	(.012)**
Experience^2 (years^2/100)		-.030	-.034	-.019	-.018	-.026	-.025	-.027	-.026	-.015
		(.021)	(.021)	(.030)	(.030)	(.031)	(.031)	(.034)	(.031)	(.031)
Education (years)		-.066	-.071	-.028	-.025	-.081	-.076	-.080	-.077	-.027
		(.024)***	(.024)***	(.061)	(.060)	(.076)	(.073)	(.000)	(.000)	(.060)
Education^2 (years^2/100)		.917	.843	.839	.795	1.079	1.054	1.095	1.064	.791
		(.159)***	(.165)***	(.168)***	(.167)***	(.276)***	(.230)***	(.369)***	(.240)***	(.171)***
Educ Control				-.044	-.031	-.016	-.019	-.026	-.021	-.029
				(.058)	(.057)	(.063)	(.063)	(.091)	(.064)	(.058)
Past apprentice	-.107	-.002	.028	.025	.037	.546	.491	.511	.497	.502
	(.065)	(.063)	(.064)	(.062)	(.062)	(.419)	(.351)	(.503)	(.348)	(.367)
App x (Ed-$\bar{E}$d)					-.052			.033	.008	-.051
					(.020)***			(.232)	(.066)	(.021)**
Raven's score			.020	.018	.019	.021	.021	.020	.021	.020
			(.008)**	(.008)**	(.009)**	(.009)**	(.009)**	(.010)**	(.009)**	(.009)**
App Control										-.478
										(.367)
Obs.	931	931	931	931	931	931	931	931	931	931
R^2	.007	.167	.182	.182	.188	.13	.14	.125	.137	.189
Education Control Function	no	no	no	yes	yes	yes	yes	yes	yes	yes
Apprentice Treatment Effect	no	no	no	no	no	yes	yes	yes	yes	no
Apprentice Control Function	no	no	no	no	no	no	no	no	no	yes
Method	OLS	OLS	OLS	IV	IV	IV	IV	IV	IV	IV

Standard errors in columns [1]-[3] are heteroscedasticity robust. Standards errors in columns [4]-[10] are bootstrapped to 1000 repetitions. "Educ control" is the predicted residuals from a first stage control function for education. "App control" is the predicted residuals from a first stage control function for apprenticeship. Regressions in columns [2]-[10] also include controls for other skills (mathematics, English and reading) as well as city dummies. *, ** and *** indicate significance levels of 90%, 95% and 99%, respectively.

Altogether, the results in Table 7 suggest a positive impact of apprenticeship on earnings for those with very low levels of education. This return is heterogeneous and declines with the level of education. The range in how much apprenticeships pay off may indicate that different kinds of people enter apprenticeship at different points. Lower ability people get into apprenticeship later on in their lives only after acquiring some formal education; they exit education before secondary school because they are not academically successful enough to continue. A different group of relatively bright people who cannot afford long-term schooling costs choose to enter apprenticeships earlier after little or no schooling. These people might have done even better to pursue formal education but were unable to do so because of limited access to credit. In sum, although low ability explains why some apprentices earn a low return, credit constraints also explain the pattern seen in the results.

In addition, there is no evidence of an upward bias due to aptitude for apprenticing. On the other hand, there is some evidence of a downward bias to the OLS estimates due to omitted unobserved ability. However this evidence is weak, as both the Wu-Hausman F-test of endogeneity and the insignificance of the App Control term in Column [10] indicate that instrumenting is not ultimately necessary. A possible explanation may be the elements of ability that remain unobserved to us only affect one's return to apprenticeship (and not one's earnings without an apprenticeship). Or alternatively this could indicate that the selection mechanism is captured through observed education—so once we have controlled for the interaction between education and apprenticeship, there is no remaining unobservable selection to correct. In either case, the OLS estimates would provide an unbiased estimate of the return to apprenticeship (for those that do it).[17]

[17]Note that the results are extremely sensitive to the choice of instruments—it is possible to find a significant result with different instruments but we endeavor here to be very strict with our instrumenting strategy in an effort to produce non-spurious results.

6.2 Gender differences

We have not yet explicitly considered the gender difference. However, men and women do not do the same type of apprenticeships. Women train almost exclusively in tailoring or hairdressing. Men tend to train in manufacturing as mechanics, carpenters and metal workers, though some also do craft-working and tailoring. Thus the type of skills acquired in the apprenticeship system varies systematically along gender lines, as does the type of firm entered afterwards.

We explore several ways in which we could capture a gender effect, if one exists. First, we introduce an interaction term between apprenticeship and gender, which is insignificant in all models. Second, we investigate different specifications with gender interaction terms (interacted with the exogenous dependent variables). The results are not sensitive to these changes. Third, we run the same regressions as in Section 6.1, but do them separately for men and women.[18] These results are presented in Tables 8 and 9. The coefficient on the past apprentice dummy is now higher for men than for women, though not statistically different.

We suggest three reasons why this may be true. First, we know that the return to apprenticeship falls as education rises. Girls who do apprenticeships are, on average, more educated than boys who do apprenticeships, and this is one reason why they experience lower returns. Second, it may be that the skills that women acquire in apprenticeship are not as valuable. Apprenticeships for women thus contain much less training than apprenticeships for men, and are therefore worth much less in the labour market. Thirdly, the return to apprenticeship may come in a different form for girls. Specifically, it may be true that women see the return to apprenticeship through a higher probability of finding a job. We explored this hypothesis briefly as an extension of this work and it does appear that in a very simple probit of labour participation in which working is regressed on apprenticeship, education, education squared, age and age squared, the marginal effect of doing an apprenticeship is nearly twice as high for women as men (16% versus 9%). On the other hand, women who do apprenticeships are not more likely to be married, or to work in a particular sector. Further exploration of these ideas is left for another paper.

[18] The first stages are run separately as well.

Table 8: **MEN only - dependent variable: ln(earnings)**

					Model 2a	Model 1a	Model 1b	Model 2b	Model 2c	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln(hrs worked per week)		.221 (.099)**	.193 (.102)*	.194 (.105)*	.205 (.104)**	.164 (.120)	.163 (.116)	.183 (.135)	.171 (.131)	.174 (.107)
Experience (years)		.020 (.015)	.018 (.014)	.015 (.016)	.012 (.016)	.008 (.018)	.008 (.018)	.013 (.021)	.007 (.019)	.004 (.017)
Experience^2 (years^2/100)		-.018 (.032)	-.011 (.031)	.00007 (.038)	.008 (.038)	.016 (.043)	.016 (.042)	.005 (.052)	.020 (.047)	.027 (.040)
Education (years)		-.081 (.034)**	-.089 (.034)***	-.058 (.067)	-.037 (.068)	-.097 (.078)	-.097 (.077)	-.072 (.000)	-.083 (.000)	-.043 (.069)
Education^2 (years^2/100)		.900 (.208)***	.879 (.210)***	.874 (.213)***	.803 (.213)***	1.135 (.334)***	1.138 (.278)***	.965 (.531)*	1.082 (.362)***	.807 (.218)***
Educ Control				-.033 (.062)	-.033 (.062)	-.024 (.064)	-.024 (.068)	-.030 (.069)	-.024 (.069)	-.028 (.062)
Past apprentice	-.100 (.086)	.008 (.086)	.070 (.086)	.069 (.089)	.044 (.089)	.640 (.572)	.647 (.447)	.264 (.699)	.597 (.456)	.611 (.474)
App x (Ed-$\bar{\text{E}}$d)					-.057 (.030)*			.002 (.274)	-.032 (.148)	-.056 (.031)*
Raven's score			.028 (.010)***	.028 (.010)***	.027 (.009)***	.027 (.011)***	.027 (.011)**	.028 (.012)**	.027 (.011)**	.026 (.009)***
App Control										-.584 (.459)
Obs.	415	415	415	415	415	415	415	415	415	415
R^2	.023	.126	.17	.171	.178	.081	.079	.16	.096	.18
Education Control Function	no	no	no	yes	yes	yes	yes	yes	yes	yes
Apprentice Treatment Effect	no	no	no	no	no	yes	yes	yes	yes	no
Apprentice Control Function	no	no	no	no	no	no	no	no	no	yes
Method	OLS	OLS	OLS	IV	IV	IV	IV	IV	IV	IV

Standard errors in columns [1]-[3] are heteroscedasticity robust. Standards errors in columns [4]-[10] are bootstrapped to 1000 repetitions. "Educ control" is the predicted residuals from a first stage control function for education. "App control" is the predicted residuals from a first stage control function for apprenticeship. Regressions in columns [2]-[10] also include controls for other skills (mathematics, English and reading) as well as city dummies. *, ** and *** indicate significance levels of 90%, 95% and 99%, respectively.

Table 9: **WOMEN only - dependent variable: ln(earnings)**

					Model 2a	Model 1a	Model 1b	Model 2b	Model 2c	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln(hrs worked per week)		.140 (.084)*	.133 (.085)	.133 (.088)	.137 (.088)	.142 (.098)	.144 (.099)	.146 (.113)	.143 (.098)	.143 (.092)
Experience (years)		.034 (.013)***	.042 (.013)***	.042 (.015)***	.041 (.015)***	.046 (.022)**	.047 (.020)**	.051 (.025)**	.048 (.022)**	.043 (.017)**
Experience^2 (years^2/100)		-.039 (.027)	-.051 (.027)*	-.049 (.037)	-.049 (.039)	-.058 (.049)	-.060 (.045)	-.064 (.052)	-.060 (.047)	-.051 (.038)
Education (years)		-.078 (.035)**	-.070 (.036)*	-.065 (.081)	-.069 (.084)	-.091 (.124)	-.096 (.111)	-.108 (.000)	-.097 (.000)	-.069 (.079)
Education^2 (years^2/100)		1.118 (.253)***	.908 (.279)***	.910 (.288)***	.878 (.289)***	.995 (.423)**	1.012 (.386)***	1.084 (.533)**	1.034 (.674)	.874 (.275)***
Educ Control				-.005 (.079)	.011 (.081)	.012 (.103)	.016 (.094)	.013 (.123)	.011 (.092)	.011 (.080)
Past apprentice	-.164 (.088)*	-.009 (.093)	-.002 (.095)	-.003 (.097)	.034 (.097)	.200 (.654)	.241 (.574)	.327 (.722)	.246 (.918)	.145 (.546)
App x (Ed-$\bar{\text{E}}$d)					-.049 (.027)*			.037 (.265)	.020 (.101)	-.048 (.027)*
Raven's score			.008 (.014)	.008 (.014)	.010 (.015)	.011 (.016)	.011 (.016)	.011 (.018)	.011 (.017)	.010 (.015)
App Control										-.114 (.565)
Obs.	516	516	516	516	516	516	516	516	516	516
R^2	.007	.088	.1	.1	.105	.093	.09	.068	.083	.105
Education Control Function	no	no	no	yes	yes	yes	yes	yes	yes	yes
Apprentice Treatment Effect	no	no	no	no	no	yes	yes	yes	yes	no
Apprentice Control Function	no	no	no	no	no	no	no	no	no	yes
Method	OLS	OLS	OLS	IV	IV	IV	IV	IV	IV	IV

Standard errors in columns [1]-[3] are heteroscedasticity robust. Standards errors in columns [4]-[10] are bootstrapped to 1000 repetitions. "Educ control" is the predicted residuals from a first stage control function for education. "App control" is the predicted residuals from a first stage control function for apprenticeship. Regressions in columns [2]-[10] also include controls for other skills (mathematics, English and reading) as well as city dummies. *, ** and *** indicate significance levels of 90%, 95% and 99%, respectively.

7 Rate of return analysis

We have found that doing an apprenticeship leads to a rise in earnings, the size of which depends on one's level of education. These returns seem at first to be quite high, so we include a rate of return analysis here to show that the point estimates found in the regressions are not unreasonable.

In Table 10 we calculate the internal rate of return (IRR) for the apprenticeship investment. Two groups are compared: those with zero education and those with 10 years of education. We find the IRR by calculating the difference in earnings predicted by the regression results in Tables 7 and thus the table shows a range of estimates. The calculation is done on an annual basis assuming a three year apprenticeship, during which the apprentice loses the median annual income for his/her level of education. These foregone earnings are actually the bulk of the cost of the apprenticeship, as the upfront fee is low relative to that (or in about 20% of the cases is nothing at all). When we assume a positive fee, we take the mean of the fees reported by current apprentices in the 2006 GUPHS. This is the most accurate valuation of current fees available.[19] The predicted earnings are evaluated at every year, at the corresponding level of experience, for 30 years. The IRR is the rate at which the net present value of the investment just equals zero.

This analysis is rough and is not meant to convey exact rates of return. We use only the point estimates in the calculation and do not evaluate the returns at the edges of the confidence intervals for each estimate. Nevertheless, these internal rates of return seem sensible. People break even on their apprenticeship investment after about 7 or 8 years of working. Compared with the real return on education, the figures in Table 10 shed some light on why formal education may be preferable to apprenticeship, especially for those students who have survived past primary school. However, those who end up doing an apprenticeship without formal education

[19]These fees, when put into 1998 cedis, are close to what is reported in the GLSS 4 as well. We also have data on what former apprentices paid for their apprenticeships but we feel that the exercise to put these values into real terms introduces too much noise into the variable.

Table 10: Internal Rate of Return

	No education	10 years of education
Assuming median upfront master fee (500,000 cedis):		
Model 2a	11.6%	na
Column [10]	22.1%	10.2%
Assuming no upfront master fee:		
Model 2a	12.0%	na
Column [10]	23.3%	10.5%

IRR evaluated with the predicted values from models in Table 7. Median fee is that reported by current apprentices in the 2006 GUPHS. Median income for those with no education is assumed to be 410,000 cedis and for those with 10 years it is 600,000 cedis. "na" means that the IRR does not exist (i.e. the investment is never recovered).

do markedly better than similarly uneducated workers who do not do an apprenticeship.

8 Summary and conclusion

Apprenticeship is, on the basis of our survey and other Ghanaian data sources, by far the most important form of training in urban Ghana. Of the training events our survey identified, over half were either current or past apprenticeships. The vast majority of apprenticeships are undertaken by those with junior high school or less. Given the prevalence of apprenticeship as a form of training in Ghana, as well as its important role in the growing informal sector, a natural question is whether apprenticeship pays off for those people who undertake it.

Our earnings data suggest that those who did an apprenticeship earn less than those with no training. This apparent paradox is suggestive of a selection story. We have investigated how far ability, credit constraints and formal education can explain this outcome. Three dimensions of ability have been modeled. The first is that observable in our data as a result of Raven's, literacy and numeracy tests. The second two dimensions of ability we have termed general ability and an aptitude for apprenticeship. We seek to identify their possible effects by using different instrumenting procedures for the apprenticeship dummy variable. Our instruments are designed, in part, to capture the possible role that credit constraints play in the decision to invest in apprenticeship. The final element we have investigated is the role of formal education in the return to apprenticeship.

We limit our sample in order to make meaningful comparisons between workers with earned income who do an apprenticeship and those who do not. We find that controls for observable ability do change the return to undertaking apprenticeship to be positive but it remains low (and insignificant). By far the most important factor affecting the return to apprenticeship is the level of formal education of those undertaking the apprenticeship. Our most conservative estimate implies that for currently employed people, who did apprenticeships but have no formal education, the training increases their earnings by 50%. The return declines as education rises. It is possible these education levels are closely related to what we have termed general ability. Those who enter apprenticeship with no formal education may well be atypically able while those who enter it with junior high school are generally low ability.

Our instrumenting procedure is designed to allow for the possibility that unobserved general ability, not fully captured by the education variable, may be biasing down the returns to apprenticeship. However we have noted that if the unobserved ability in the data is what we have termed "an aptitude for apprenticing" then the bias in the estimate on the apprenticeship dummy will be upwards. While we cannot reject the hypothesis that apprenticeship is exogenous we interpret the evidence as showing that the OLS estimates with controls for formal education are a lower bound for the return to apprenticeship. The first stage regression can be given an interpretation as showing a role for credit constraints in the decision to undertake apprenticeship, although its importance relative to the roles of general ability and aptitude remains an open question.

We conduct a rate of return analysis which provides a check on the point estimates and shows that the regression results imply rates of return of up to 20% if we are willing to accept the point estimates from instrumenting. In addition, we find that men who do apprenticeships earn higher returns than women who do them, though this difference is not significant. The increment in earnings is only one aspect of the return to apprenticeship and these other aspects, an increased probability of a job and its social role, may be more important for women than men.

Our analysis has shown that for some choosing the apprenticeship route can yield a high return. Nonetheless, the fact that we identify a positive impact of apprenticeship on earnings should not distract us from the bigger picture, which is that workers who did an apprenticeship are now earning less than other workers who did not do this type of training. We are not able to model here the feedback effects that mean that apprentices are still not "succeeding", in terms of earnings, in the overall labour market. There is something else that then causes their low earnings. Poor earnings for apprentices may result from two factors: unobservable individual characteristics and unobservable workplace characteristics. We have explored the first factor in this paper as an explanation for selection into the apprenticeship system. The second factor depends on how trained apprentices move through the labour market. Entering the apprenticeship system puts workers on a path to the informal sector and shuts them out of more lucrative formal sector jobs. Indeed, qualitative studies find that apprentices tend to be isolated from formal wage employment. This issue raises further questions about the effect of apprenticeship on occupational choice as well as questions as to what causes the market segmentation that is so characteristic of labour markets in Africa. Exploration of these questions is left to future research.

A Apprenticeship in Ghana

Traditional apprenticeships in West Africa are widespread. In Ghana, the practice is particularly common, especially in the informal sector. The market for apprenticeships is more established and has flourished over time.

Although every apprenticeship is different, in general a written or oral agreement is made between the "master" or "mistress" and the parents/guardians of the potential apprentice. The education of an adolescent is effectively transferred from the parent to the master (Boehm, 1995). As a result, apprenticeships are as much socialization as training. Often, the master will receive a fee, but other times the apprentice will work for reduced (or no) wages. Entry is for the most part open for anyone who can pay the training fee: minimum education requirements are non-existent, and other necessary qualifications besides ethnic or clan identity are uncommon (Middleton et al., 1993). Skills transfer occurs mainly by watching and imitating the master (Johanson & Adams, 2004). The apprenticeship usually lasts for a fixed term (typically 3 or 4 years).

The nature of the training is sector-specific and often product-specific; apprentices may learn how to manufacture only one item, for example (Frazer, 2006). They also learn trade-related skills such as how to handle tools and repair machines, as well as general business management skills like sourcing, pricing, and contracting. Relative to more formal vocational training, apprenticeships are much more flexible. Apprentices also have more relevant skills because they do hands-on work as opposed to classroom training.

Nearly all apprentices want to set up their own business after their training is completed, as this is by far the most rewarding outcome. However, this may require substantial start-up capital, especially in manufacturing.

B First stage IV results

Included below are the relevant first stage results, including test statistics for the first stage of the IV (Model 1a).

Table 11: **First Stage Control Function for Education - dependent variable: education (years)**

Ln(hrs worked per week)	-.162 (.205)
Male	.509 (.202)**
Experience (years)	.055 (.026)**
Experience (years^2/100)	-.288 (.052)***
Brother's education (years)	.080 (.028)***
Sister's education (years)	.078 (.030)**
Cape Coast	1.297 (.576)**
Accra	-.387 (.303)
Kumasi	-.505 (.314)
Raven's score	.045 (.024)*
English Score	.149 (.017)***
Reading Score	.046 (.029)
Math Score	.098 (.032)***
Obs.	931
R^2	.501
F statistic	83.144

Standards errors are robust.

Table 12: **First Stage Probit for Apprenticeship - dependent variable: apprenticeship (dummy)**

Ln(hrs worked per week)	.014
	(.107)
Male	.127
	(.110)
Experience (years)	-.014
	(.018)
Experience (years^2/100)	.004
	(.048)
Education (years)	.416
	(.100)***
Education^2 (years^2/100)	-2.378
	(.360)***
Number of other apprentices in HH	.252
	(.082)***
Piped internal water in home	.298
	(.101)***
HH borrowed in past year	.252
	(.127)**
Cape Coast	-.994
	(.309)***
Accra	-.109
	(.157)
Kumasi	-.177
	(.168)
Raven's score	-.015
	(.014)
English Score	.022
	(.017)
Reading Score	.001
	(.021)
Math Score	-.102
	(.023)***
Educ Control	-.155
	(.094)*
Obs.	931
Log Likelihood	-468.407

Standards errors are robust.

Table 13: **Identification check for apprenticeship instruments - dependent variable: education (years)**

Male	1.460 (.218)***
Experience (years)	-.036 (.032)
Experience (years^2/100)	-.193 (.064)***
Brother's education (years)	.121 (.032)***
Sister's education (years)	.178 (.032)***
Number of other apprentices in HH	-.458 (.184)**
Piped internal water in home	.462 (.229)**
HH borrowed in past year	.379 (.304)
Cape Coast	1.619 (.655)**
Accra	-.190 (.324)
Kumasi	-.805 (.344)**
Obs.	931
R^2	.35

Standards errors are robust.

Table 14: **Test statistics for Model 1a (IV)**

First stage F-statistic, distributed as $F_{(15,915)}$	16.37
P-value	0.000
Hansen J-statistic (overidentifying test), distributed as $\chi^2_{(2)}$	0.411
P-value	0.8143
Difference in Sargan-Hansen statistics (endogeneity test), distributed as $\chi^2_{(1)}$	1.798
P-value	0.1800

These test statistics are robust.

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