Learning & Earning in Africa: Evidence from Ghana*

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Abstract

This paper investigates the sources of rising lifetime incomes in Ghana using both existing cross-section data and a new panel data set which allows us to measure earnings growth within jobs and to construct lifetime work histories for both wage employees and the self-employed. In Ghana - as elsewhere in sub-Saharan Africa - the non-rural self-employed constitute the most rapidly growing part of the urban labour force. Cross-sectional estimates of Mincerian wage earning equations show a concave relationship between experience and earnings, as is found in virtually all datasets, and a strongly convex relationship between education and earnings. We establish that similar cross-section age and tenure patterns exist for both the self-employed and wage employees. We then investigate the sources of these age-earnings profiles using time spent working, rather than age, as our measure of experience and testing if the cross-section data reflect within-job earnings growth. We find evidence of substantial bias in the cross-section estimates. The implications of these biases for earnings growth of the self-employed relative to wage employees are discussed.

*This paper draws on data collected by the Centre for the Study of African Economies, Oxford, in collaboration with the Ghana Statistical Office (GSO), Accra over a period from 2003 to 2005. The surveys have been funded in part by the Department for International Development of the UK. Work on this project was also funded by the Economic and Social Research Council of the UK as part of the Global Poverty Research Group. We are greatly indebted to numerous collaborators for enabling this data to be assembled.

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1 Introduction

A central issue in understanding growth in poor countries and how this is related to poverty reduction is the relationship between human capital investment and earnings. Three dimensions of this investment in human capital have been very extensively investigated - that arising from formal education and that due to general and specific work based experience. In this paper we estimate the determinants of rising lifetime incomes in urban Ghana, focusing on the ability of human capital theory to explain earnings increases in panel data.

As we will show, the cross-section evidence for Ghana suggests that the returns from general work experience, as measured by age, and from specific work experience, as measured by job tenure, are substantial – approximately twice as large as the returns found in U.S. data for instance (Topel 1991, Altonji and Williams 1997). Do these steep age and tenure profiles reflect the actual life-cycle earnings pattern of a "typical" Ghanaian worker? Are there significant differences in these patterns between wage employees and the self-employed? Currently the self employed, who are often excluded from labor market analysis, outnumber wage earners by roughly two-to-one in urban Ghana. Finally, to what extent do the substantial earnings differences between young and old workers which we observe in cross-sectional data reflect a process of human capital acquisition? The answers to these questions have direct implications for our understanding of labor mobility in poor countries and, by extension, poverty dynamics.

Conceptually we can distinguish two routes by which workers' earnings may rise over time. First, workers who remain in a given job may accrue returns to tenure, reflecting the acquisition of job-specific human capital through learning-by-doing; similarly, all workers regardless of job movement may acquire general human capital through work experience. This process of human capital acquisition, which we refer to as the "learning hypothesis", has provided the dominant interpretation of experience and tenure effects on earnings since Becker's (1964) seminal work in the area.

Alternatively, workers' earnings may rise as they switch to new jobs in pursuit of higher earnings opportunities. As shown in the following section, such behavior can mimic observed earnings profiles quite well, particularly if imperfect information and other labor market frictions imply that workers move incrementally over considerable time toward their highest earnings opportunities. This second channel of earnings growth is frequently associated with the selection model of Roy (1951). Crucially, the Roy framework can explain positive age- and tenure-earnings profiles without recourse to learning or human capital acquisition.

A recent body of research on earnings growth in developed economies began with Topel (1991). Using longitudinal data for the U.S. (the Michigan Panel Study of Income Dynamics) Topel estimated a return to seniority of .223 over ten years based on within-job earnings growth. However, after relaxing some of Topel's assumptions about the exogeneity of work experience in the earnings equation, Altonji and Williams (1997) present an alternative estimate of .126 using the same data source.

A recent study by Buchinsky, et al (2005) clarifies the two separate sources of selection bias plaguing attempts to estimate returns to tenure and experience. The first type of selection arises from the endogeneity of labor force participation to earnings. This sort of selection is particularly relevant for estimates of age- and general experienice-earnings profiles. The second type of selection relates to the endogeneity of the job-switching decision, as discussed in detail in the following section. Endogenous job-switching has direct implications for the correlation between earnings and job tenure. For the U.S., Buchinsky, et al find that simultaneous estimation of earnings, participation and job-switching equations yields returns to seniority closer to Topel's initial, larger point estimates.

In this paper we focus on the second source of selection bias.[1] We use panel data of individual job histories to distinguish between these alternative hypotheses – learning and selection – as explanations of life-cycle earnings patterns in urban Ghana. Section 2 develops a simple model of wage determination and job mobility incorporating both learning and selection effects. In section 3 we present descriptive estimates of the relationship between

[1]In principle, our data allows us to address the endogeneity of both job-switching and labor force participation. It is hoped that this extension will be incorporated in subsequent versions of the paper.

earnings and experience using existing cross-sectional data sources. Section 4 estimates this model with a new panel data set and section 6 concludes.

2 A Model of Earnings and Job Mobility

Suppose the earnings of worker i in job j at time t are determined by the following equation:

$$\ln w_{ijt} = \beta_1 X_{ijt} + (\beta_2 + \beta_{2ij})T_{ijt} + \mu_i + \phi_{ij} \tag{1}$$

The first term reflects the acquisition of general human capital through learning on the job, i.e., the causal impact of experience, X, on earnings. Similarly, the second term depicts the acquisition of job-specific skills over the course of a worker's job tenure, T. The β_{2ij} term allows for heterogeneity in these returns to tenure, consistent with the idea that some jobs provide greater opportunity for learning (and income growth) than others. The third term, μ_i, allows for variation across individuals in general skills.

The last term in (1), ϕ_{ij}, is frequently referred to in the earnings literature as the quality of a job match. This reflects the idea that individuals with given characteristics will have different earnings in different jobs. The returns to a job match may reflect economic rents or simply the marginal product of job-specific skills. In either case, the key point is that ϕ_{ij} is assumed to be fixed for the duration of job j.

So far we have modeled earnings as the outcome of a passive learning process. We also wish to incorporate optimizing behavior on the part of workers, building on Roy's (1951) model of endogenous job switches.[2] The central feature of the Roy model is the idea that workers move occupation or industry over time in search of the best available earnings opportunities. Here we model job mobility as the result of a simple search process. In addition to earnings from their current job (w_{ijt}), workers also receive an alternative earnings opportunity each period (w_{ikt}). This outside option is

[2] See Heckman and Honore (1990) and Borjas (1987) for empirical applications of the Roy selection model. Suri (2005) uses a similar framework to the one we apply here in her investigation of fertilizer adoption decisions by Kenyan farmers based on heterogenous returns.

comprised of a random draw from the prior distribution of the ϕ and β_2 terms. At the beginning of the period workers choose whether to stay in the current job or accept the new offer. Examining the terms in equation 1 we can see that the two earnings opportunities may differ in three respects:

1. the new earnings draw may pay a different, time-invariant job match premium ($\phi_{ij} \neq \phi_{ik}$)
2. the new opportunity may offer a different rate of earnings growth ($\beta_{2ij} \neq \beta_{2ik}$)
3. by definition, switching to a new job will imply starting over with zero tenure ($T_{ijt} > T_{ikt} = 0$).

Under the assumption of income maximization workers will move to a new job if the discounted present value (DPV) of the new opportunity exceeds the DPV of the current job

$$\sum_{s=t}^{S} w_{iks} \frac{1-\delta^s}{1-\delta} > \sum_{s=t}^{S} w_{ijs} \frac{1-\delta^s}{1-\delta} \tag{2}$$

calculated over the remainder of a worker's career of S periods. This inequality will hold inasmuch as the increased level or growth rate of earnings in the new job outweigh the accumulated returns to tenure in the present job.

What can we say about the time path of earnings and job movement that will result from this model? First, for a given individual it is clear that within-job earnings growth will equal the sum of the experience and tenure terms, $\beta_1 + \beta_2 + \beta_{2ij}$. Second, earnings increases over the life-cycle will reflect not only the returns to experience, but also the gains from job mobility. If new job match opportunities (draws of ϕ_{ik}) are genuinely random, we can expect that job mobility will slow over a worker's career, and that the age-relationship will be somewhat concave, as the potential for improved job matches diminishes over time.

3 The Determinants of Earnings from Cross-Section Data

Our first data source is the Ghana Living Standard Surveys (GLSS, (GSO 1987-1998)) which have been conducted in four years covering the period from 1987/88 to 1998/99. In Table A-6 this data is presented both for the whole economy and for the urban sector. (Our analysis of the data will be confined to the urban sector to ensure comparability between the GLSS data and the panel data to be presented below.) The main point to take away from the table is the substantial rise in urban self-employment in Ghana, a trend which mirrors the experience of several other African countries (Kingdon, Sandefur, and Teal forthcoming). Between 1987/88 and 1998/99 the labour force expanded by nearly 2.4 million and all the new jobs were either in non-rural self employment or farming. In proportional terms the growth in non-rural self-employment was by far the largest with the number of jobs doubling over this ten year period. This trend highlights the importance of understanding differences in the earnings structure of wage employees and the self-employed. Accordingly, all of the regression results presented below are disaggregated by these two broad occupational categories.

Our basic empirical specification is a standard Mincerian earnings equation in which we use earnings data for both the self-employed and wage employees:

$$\ln w_{ij} = \beta_0 + \beta_1 X_{ij} + \beta_2 T_{ij} + \beta_3 \mathbf{Z}_{ij} + \varepsilon_{ij} \qquad (3)$$

where X is work experience, T is tenure in the current job, $\mathbf{Z}$ is a vector of controls, and the subscripts i and j index individuals and jobs, where we distinguish only between wage jobs and self-employment activities. The problems posed in estimating equation (3) where unobservables are correlated with both experience and tenure will be taken up in the next section where the panel data that allows some of these issues to be addressed is introduced.

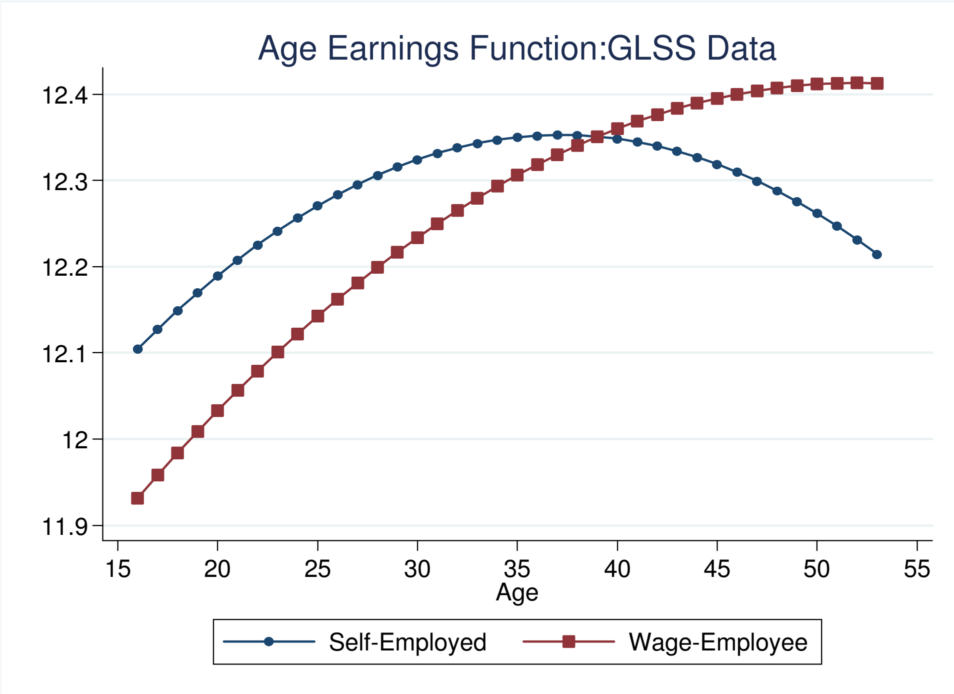
In Table A-7 we report the descriptive statistics for the samples drawn from the GLSS that will be used for estimating both equations. We are confined to the first three of the GLSS surveys as for the fourth one conducted in 1998/99 questions related to tenure were not asked. We confine the sample to individuals who either have a private sector wage job or are classified as non-rural self-employees and for whom we have complete data on earnings, gender, age, education, tenure and the parental characteristics that enter the education and job choice equations. Table A-7 shows that we have 2,708 observations and presents the data broken down by gender. In Table A-8 we report our estimates of equation (3) for the GLSS. In Figure 1 we show both the relationships between earnings and age, our measure of general work experience, and tenure, which is the length of time spent in the job implied by the regressions in Table A-8.

The primary, and rather surprising, result of the comparison is that the experience and the tenure effects for both types of workers are very substantial and relatively similar. If we look at the age range from 15 to 35 earnings rise by 31% for the self-employed and by 51% for wage employees. If we look at the tenure range from 1 to 20 earnings rise by 63% for the self-employed and by 60% for the wage employees. If the returns to tenure reflect learning within the job, there appears to be as much learning occurring within self-employment as in wage jobs.

In addition, we note that our results are consistent with existing work estimating earnings equations on the GLSS data, but very different in focus. The work by Glewwe (1999) and Jolliffe (1998) focuses on the causal interpretation of the education coefficient in (3). Our interest in the present paper is primarily in the age and experience coefficients which appear to play an equal or even greater role in earnings determination in the cross section.

4 Earnings Growth in Panel Data

The returns to tenure and experience presented so far are based on cross-section data. However, there are obvious pitfalls to inferring patterns of rising incomes from such data. In the introduction we posed two questions about these patterns to which we return in this section. First, are these tenure and experience effects causal, in the sense that they might represent



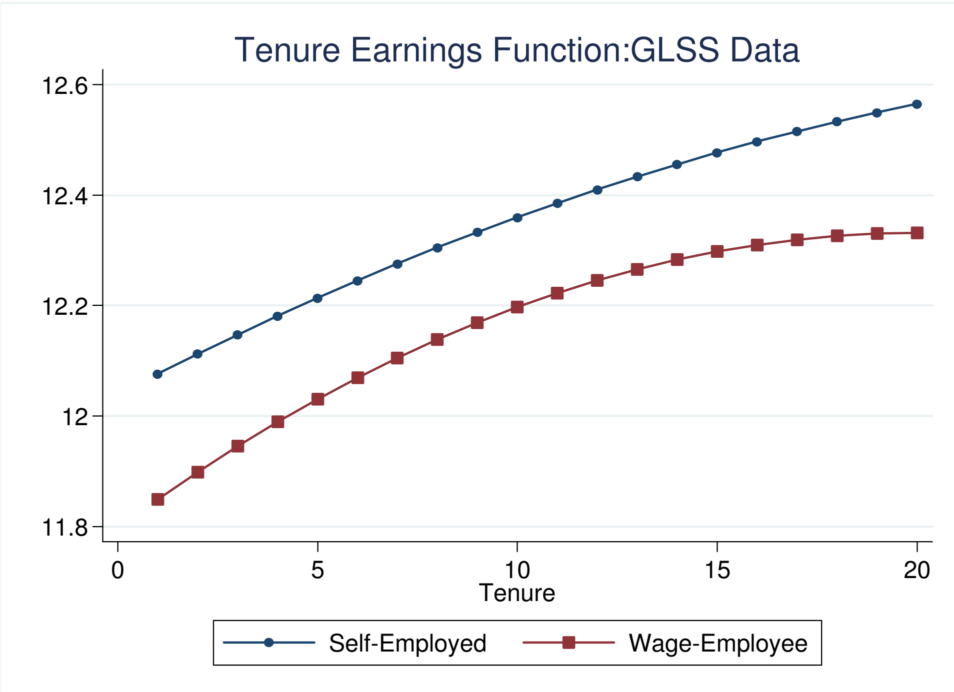


Figure 1: Earnings shown in the Figure is ln(Monthly Earnings in 1998 Cedis) The data is pooled across the first three waves of the GLSS Data - 1987/88 -1991/92.

a learning effect as suggested by Becker? Second, regardless of whether we are observing a learning process or simply endogenous job switching, we are interested in whether these estimates are an indication of the earnings growth which a given individual can expect to achieve over time. This latter question relates to biases in cross-section measurement, the former to testing theoretical models which can explain earnings growth.

4.1 Data

Our data source that enables us to tackle some of the problems of interpretation posed by the use of cross-section data is a labour market survey conducted initially over the period from October 2003 to July 2004 by the CSAE in collaboration with the Ghana Statistical Office - the Ghana Worker Household Survey (GHWS). The GLSS surveys are intended to be nationally representative. In contrast the GHWS is confined to the major urban areas in Ghana - Accra, Kumasi, Takoradi and Cape Coast. The GHWS draws individuals from a random sample of households in selected neighborhoods.

During the course of July-August 2005 the initial GHWS sample was resurveyed and questions were asked which enabled us to link their activities and earnings in 2005 with the same variables in 2003/04. At the time of the first interview respondents were asked for their job histories since leaving school. As part of this recall data they were asked their earnings when they started a job and when they finished one. This procedure ensured that we have data for earnings at the start of a job when, by construction, tenure is zero. This procedure also enabled us to create actual work experience variables by summing time in the labour force. Figure 2 provides a stylized representation of an individual work history as observed in the GHWS dataset.

In the results which we will present below we make use of three samples which can be created from this data. The first we term "observed" by which we mean that the earnings were those reported at the time of the interviews in 2003/04 and 2005, they are observed in the sense that they are not based on recalling the past. The second sample is based on recall data for earnings at the end of their past job and the third sample is based on recall data for

Table 1: Summary Statistics for GHWS Regression Sample

	mean	median	min	max
US$ earnings/mo.	77.90	59.63	2.98	894.52
US$ earnings/mo. (start of job)	105.36	50.38	2.98	894.40
Proportion wage employees	.32	0	0	1
Proportion males	.43	0	0	1
Age	34.79	33.95	16	67.04
Years of education	8.60	10	0	20
Years of tenure	9.99	7	0	44.75
Years total experience	13.19	11.29	0	56.5
Proportion managers	.08	0	0	1
# employees (Self-Employed)	.37	0	0	11
# employees (Wage Employees)	113.27	1	1	344.8

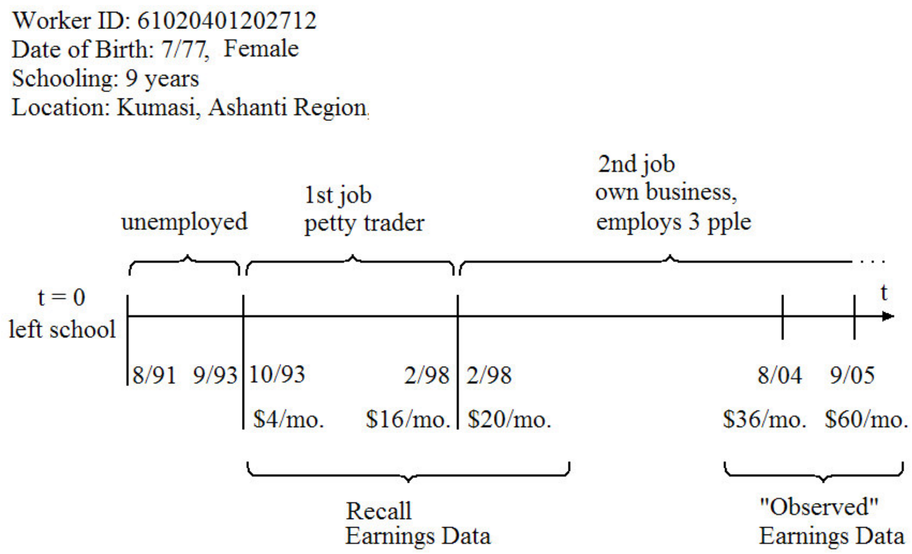


Figure 2: Stylized Representation of a GHWS Data Point

the start of earnings. Clearly we anticipate that measurement error will be a more serious problem for recall then for the “observed” data.

4.2 Potential Biases

The structure of the GHWS data allows us to investigate the importance of experience and tenure in earnings determination in greater detail, and specifically to ask whether the cross-sectional results in the previous section hold for a given individual over time. Rewriting equation (3) with time subscripts, and allowing for a linear time trend

$$\ln w_{ijt} = \beta_0 + \beta_1 X_{ijt} + \beta_2 T_{ijt} + \beta_3 \mathbf{Z}_{ijt} + \tau t + \varepsilon_{ijt} \tag{4}$$

we can decompose the unobservables in the Mincerian earnings equation as

$$\varepsilon_{ijt} = \phi_{ij} + \beta_{2ij} T_{ijt} + \mu_i + \upsilon_{ijt} \tag{5}$$

which incorporates differences in job-match quality and hetergeneity in returns to tenure, as outlined in section 2.

The potential selection bias in estimates of β_2 can arise from at least two different sources, corresponding to the ϕ_{ij} and the β_{2ij} terms in (5) and requiring distinct empirical strategies.

1. Bias due to a correlation between tenure and ϕ_{ij}. For a given worker in a given job ϕ_{ij} is time invariant. However, workers with higher values of ϕ_{ij} (i.e., workers with a better job-match yielding a higher wage for a given vector of personal characterisitics) may be less likely to exit. As a result, the average value of ϕ_{ij} among workers in a given job will be rising over time with tenure (biasing β_2 upward). Conversely, new entrants to a job will presumably have switched in pursuit of a better job match. Thus workers with low tenure will have disproportionately high values of ϕ_{ij} (biasing β_2 downward). In either case, our fundamental problem is that $\phi_{ij} \neq 0$ for workers who accrue job tenure.

   One strategy to eliminate this bias is to difference equation (4) to yield

   $$\Delta \ln w_{ijt} = \beta_1 \Delta X_{ijt} + (\beta_2 + \beta_{2ij}) \Delta T_{ijt} + \tau + \Delta \upsilon_{ijt}.$$

   By restricting the sample to workers who do not change jobs over the interval ('stayers'), we ensure that $\Delta X_{ijt} = \Delta T_{ijt} = 1$ which yields

$$\Delta \ln w_{ijt} = \beta_1 + \beta_2 + \beta_{2ij} + \tau + \Delta v_{ijt} \qquad (6)$$

While estimation of (6) does not permit us to separately identify the effects of tenure, experience and the time trend, it will produce an unbiased estimate of within-job earnings growth for the 'stayers'.

2. Bias due to a correlation between tenure and β_{2ij}. If workers have information about the likely rate of earnings increases in their current job (their value of β_{2ij}) it is reasonable to assume that this will influence their decision to stay or quit. If workers with low values of β_{2ij} move, this will produce a cross-sectional relationship between tenure and earnings which does not reflect the average returns available in a job. This arises because, if such a selection process is present, $\beta_{2ij} \neq 0$ among workers with high tenure. Furthermore, this bias will remain after differencing the data as in (6). However, while there appears to be no simple method to avoid the potential selection bias arising from heterogeneity in the returns to tenure, the following section presents a measure of the magnitude of this bias by comparison of the within-job earnings growth rates (equation (6)) for 'movers' and 'stayers'.

Figure 3 provides a heuristic overview of these two potential sources of selection bias. In the first panel, wages differ by the quality of job match, but returns to tenure are the same for all jobs and the job-switching decision is exogenous. In this case, cross-sectional OLS estimates of β_2 will provide consistent measures of the average return to tenure which a worker can expect ex ante. In the second panel returns to tenure are still homogenous, but the switching decision is endogenous to the quality of job match. As shown, a cross-sectional tenure effect will appear even if the return to tenure is zero, but differencing resolves this bias. Finally, in the last panel endogenous job switching is driven by heterogeneity in the returns to tenure, yielding both cross-sectional and differenced estimates of β_2 inconsistent.

In either case, the underlying source of the selection bias in the OLS coefficients is the fact that the probability of job separation λ is correlated

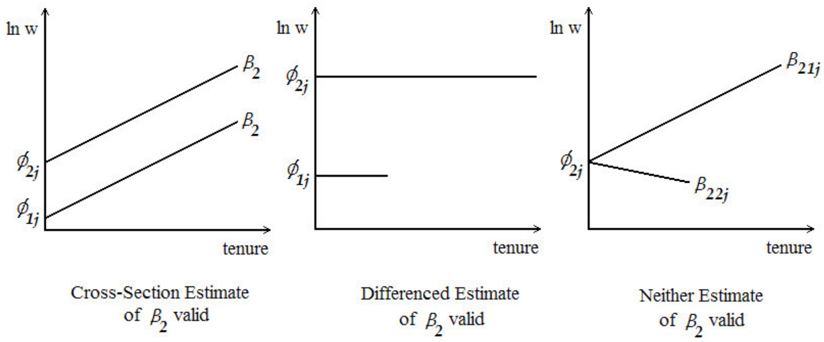


Figure 3: Alternative patterns of job tenure and unobserved earnings determinants

with the quality of job-match ϕ_{ij} and β_{2ij},

$$\lambda_{ijt} = \lambda(t, \phi_{ij(t)}, \beta_{2ij}). \tag{7}$$

While the ϕ_{ij} and β_{2ij} are unobservable, their impact is captured in the data on earnings (which incorporates ϕ_{ij} and β_{2ij}) and within-job earnings growth (which isolates β_{2ij}). Because we also have data on completed job spells, it is possible to empirically estimate the impact of earnings and earnings growth on the probability of separation.

To implement 7 we estimate the probability that a worker leaves their job in period t using a proportional hazard model, where the job separation rate is a function of the time in job and covariates. We parameterize the λ function using the Weibull distribution, which yields our empirical model of job duration:

$$\lambda_{ijt} = \rho t^{\rho-1} e^{\gamma_0 + \gamma_1 \ln w_{ijt} + \gamma_2 \Delta \ln w_{ijt} + \tau_{ijt}} \tag{8}$$

If job separations are voluntary and the income maximization hypothesis holds, we would expect to observe negative values for both γ_1 and γ_2. Furthermore, the relative importance of $\ln w_{ijt}$ and $\Delta \ln w_{ijt}$ in explaining job separations will be informative as to the source of the selection bias, with a strong effect of the latter term indicating a role for heterogeneity in the returns to tenure.

5 How Do Earnings Rise with Experience?

In Table 1 we present the structure of the data from the GHWS for 2004. For purposes of comparison with the GLSS results from Table A-8 our first estimates, reported in Table 2, use Age as the measure of work experience. Figure **??** provides an overview of the earnings distribution for the self-employed and wage employees, whom we divide between those in firms with fewer than or greater than 30 employees. The solid lines show the raw earnings distribution, based on an Epanechnikov kernel density estimator with a bandwidth of 0.5, while the dashed lines show earnings after controlling for age, education, and gender. In both cases, workers in large firms appear to earn a substantial wage premium. However, the self-employed and wage-earners in small firms have very similar earnings distributions.

In Table 2 three sets of regressions are reported. The first, in the first three columns of the Table, use what we referred to above as the "observed" data - it is the data for 2003/04 and 2005 where we asked respondents their current earnings. The three regressions reported are for the pooled data, for the self-employed and for wage earners. In columns (4)-(6) we show a similar set of regressions for the recalled earnings in all past job as the jobs ended. In columns (7)-(9) we use recall data when respondents started their job, it is for these that the tenure variable is, by construction, zero.

The results in Table 2 columns (1)-(3) differ from those in Table A-8 in that we cannot identify both an experience and a tenure effect. If we consider the total effect of experience as measured by age and tenure the patterns across the self-employed and wage employees are very similar. There is no evidence, at least for younger workers, that the returns to experience and tenure combined are not at least as great for the self-employed as they are for wage earners. This result is very similar to that obtained for the GLSS data in Table A-8. There appear to be very substantial, and concave, returns to work experience for the self-employed.

In Table 3 we replace age with a direct measure of work experience: the sum of tenure in all jobs over the course an individual's lifetime, as measured in the recall data. Columns (1)-(3) show that while there is a significant effect from this measure of experience in the pooled data, it is

Table 2: Earnings Equations in GHWS

	nowP	nowS	nowW	stopP	stopS	stopW	startP	startS	startW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
male	.216	.222	.230	-.020	.0007	-.084	.325	.357	.189
	(.044)***	(.056)***	(.076)***	(.154)	(.223)	(.217)	(.115)***	(.130)***	(.252)
educ	-.039	-.042	.027	.055	-.005	.027	.033	.050	-.199
	(.027)	(.031)	(.056)	(.089)	(.110)	(.152)	(.073)	(.080)	(.199)
educ^2	.007	.006	.005	-.002	.005	-.001	.003	.003	.015
	(.002)***	(.002)***	(.003)	(.006)	(.008)	(.009)	(.004)	(.005)	(.011)
age	.035	.032	.041	.009	-.065	.038	.029	.027	.063
	(.011)***	(.013)**	(.018)**	(.043)	(.074)	(.061)	(.026)	(.028)	(.077)
age^2/100	-.036	-.034	-.034	.011	.092	-.020	-.025	-.022	-.091
	(.012)***	(.014)**	(.020)*	(.057)	(.107)	(.079)	(.031)	(.033)	(.106)
tenure	.0009	.0004	.002	-.003	.0008	-.003			
	(.0006)	(.0008)	(.001)	(.002)	(.004)	(.003)			
tenuresq	-.00002	.00008	-.0003	.00008	-.0006	.0001			
	(.0001)	(.0002)	(.0002)	(.0006)	(.001)	(.0007)			
employees	.163	.177		.343	.386		.342	.334	
	(.027)***	(.028)***		(.142)**	(.125)***		(.068)***	(.071)***	
manager	.144		.139	.276		.306	.426		.523
	(.074)*		(.073)*	(.182)		(.213)	(.303)		(.254)**
ln(firm size)	.116		.104	.119		.118	.069		.106
	(.022)***		(.023)***	(.054)**		(.063)*	(.083)		(.065)
wage dummy	-.247			-.325			-.133		
	(.097)**			(.266)			(.358)		
trend	.067	.052	.076	-.123	-.117	-.125	-.189	-.192	-.185
	(.043)	(.054)	(.071)	(.013)***	(.019)***	(.018)***	(.010)***	(.011)***	(.019)***
Obs.	917	609	308	207	70	137	358	309	49
R^2	.34	.255	.448	.461	.574	.398	.653	.635	.828

Table 3: Earnings Equations in GHWS: Substituting Experience for Age

	Observed (Date of Interview)			Recall Data (1980 - 2005) End of Past Job			Recall Data (1980 - 2005) Start of Past Job		
	Pooled	Self Emp	Wage	Pooled	Self Emp	Wage	Pooled	Self Emp	Wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
male	.249	.266	.266	.154	.172	.171	.125	.071	.234
	(.045)***	(.061)***	(.061)***	(.139)	(.230)	(.179)	(.099)	(.167)	(.112)**
educ	-.028	-.015	.008	-.124	-.113	-.189	-.052	-.062	.011
	(.014)**	(.020)	(.023)	(.045)***	(.075)	(.080)**	(.031)*	(.048)	(.044)
$educ^2$	.004	.002	.003	.008	.008	.011	.005	.006	.002
	(.0009)***	(.001)	(.001)***	(.003)***	(.006)	(.004)***	(.002)***	(.004)*	(.002)
exper	.017	.022	.016	.001	-.002	-.029	.030	.020	.045
	(.009)*	(.014)	(.010)	(.038)	(.070)	(.075)	(.018)*	(.026)	(.024)*
$exper^2/100$	-.055	-.068	-.043	.141	.143	.313	-.093	-.058	-.169
	(.027)**	(.042)	(.029)	(.115)	(.178)	(.370)	(.081)	(.110)	(.115)
tenure	.039	.047	.012	-.044	-.022	-.112			
	(.010)***	(.014)***	(.013)	(.041)	(.072)	(.078)			
$tenure^2/100$	-.073	-.095	-.00005	.055	-.036	.415	-.093	-.058	-.169
	(.032)**	(.045)**	(.043)	(.138)	(.202)	(.393)	(.081)	(.110)	(.115)
employees	.088	.088		.476	.506		.094	.063	
	(.022)***	(.024)***		(.287)*	(.313)		(.065)	(.073)	
manager	.268		.305	.497		.567	-.070		.017
	(.085)***		(.068)***	(.204)**		(.197)***	(.148)		(.124)
ln(firm size)	.156		.144	.103		.119	.084		.113
	(.021)***		(.018)***	(.054)*		(.053)**	(.038)**		(.033)***
wage dummy	-.270			-.209			-.097		
	(.086)***			(.233)			(.156)		
trend	.088	.101	.067	-.033	-.041	-.028	-.065	-.096	-.022
	(.043)**	(.056)*	(.057)	(.013)***	(.020)**	(.018)	(.007)***	(.010)***	(.009)**
Obs.	1318	900	418	302	151	151	568	298	270
R^2	.268	.132	.531	.193	.124	.28	.238	.28	.248

Table 4: Within-Job Earnings Growth in GHWS Panel Data

	2004-05 Growth			Annual Growth Since Job Start					
				Ongoing Job Spells			Past Job Spells		
	Pooled	Self-Emp	Wage	Pooled	Self-Emp	Wage	Pooled	Self-Emp	Wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Const.	.084	.107	.038	.009	.021	-.005	-.032	-.0006	-.052
	(.022)***	(.030)***	(.029)	(.007)	(.011)**	(.009)	(.012)***	(.021)	(.014)***
age	.002	.003	-.0003	-.001	-.002	-.0004	.001	-.001	.002
	(.002)	(.003)	(.003)	(.0008)	(.001)*	(.001)	(.002)	(.003)	(.002)
Const.	.006	-.019	.047	.049	.103	.006	-.069	.042	-.114
	(.088)	(.123)	(.111)	(.028)*	(.044)**	(.035)	(.047)	(.082)	(.060)*
R^2	.003	.006	.00009	.005	.016	.0006	.004	.004	.01
Obs.	264	174	90	416	226	190	179	69	110

approximately half the magnitude of the age coefficient in the previous table and drops out of significance when we disaggregate wage employees and the self-employed. This result is surprising if one views the age-earnings profile as a measure of skill acquisition over the working career. Such skills are presumably acquired through actual work experience, as opposed to time spent out of the labour force or unemployed. While measurement error is undoubtedly a problem with the recall data, it seems unlikely that even a noisy measure of actual work experience should do worse at capturing such learning effects than raw age.

So far we have confined ourselves to the cross-section dimension of the GHWS data. Our first step toward exploiting the panel structure of the GHWS is in Table 4 where we present differenced versions of each of our three sets of regressions. In the first three columns of Table 4 we obtain the results of estimating equation (6) using two rounds of panel data from 2004 and 2005. Note that the sample here is restricted to 'stayers' who have remained in their initial job. In the last six columns of Table 4 we estimate equation (6) using recall data. Earnings growth in columns 3 to 9 is computed as the annualized difference in earnings from the start of the job until the end/most recent observation.

In the first row of Table 4 we present a simple measure of average within-job earnings growth. This measure, 8% per annum for the pooled data, represents the sum of the linear age, tenure, and trend effects for those who remain in their job, as shown in equation (6). The lower panel of results in Table 4 estimates a more general specification. It is clear that a one-year time span is not enough to identify the concavity of the earnings experience profile in the differenced specification. Nevertheless, there is evidence that within job earnings growth is at least as great for the self-employed as it is for wage earners. Further, we have some evidence from the panel that the experience earnings profile clear in the cross-section does reflect earnings growth for individuals within jobs.

The differenced specifications in columns 1-3 corrected for selection bias related to unobserved quality of job-matches, ϕ_{ij}. The right hand side of Table 4 uses the recall data to measure the potential bias from heterogeneity in the returns to tenure. Columns 4-6 report earnings growth for workers in their current job. Because we have a longer time span in the recall data, we are able to identify the concavity of the age-earnings relationship in at least one case. Workers in this sample are, by some definition, 'stayers' in that they have chosen not to exit their jobs to date. For these workers we find an initial return to tenure of 10% for the self-employed, but no significant effect for wage employees.

Finally, columns 7-9 estimate the rate of earnings growth on completed job spells. If earnings growth contributes to the job exit decision, as suggested in the previous section, we would expect to find lower returns to tenure for this group. This is indeed what we find: the point estimate of .04 for the self-employed is insignificant, and average earnings growth for wage employees is -11.4%.

Comparing the returns to tenure for ongoing vs. completed job spells in Table 4 suggests that heterogeneity in the returns to tenure may contribute to a serious selection bias in the average returns estimated in both cross-sectional and longitudinal data. While workers who stay in their jobs and accumulate tenure experience rapid earnings increases, this is a unrepresentative sample of the labor force. Those who have left their jobs showed no prospects of similar increases.

Finally, Table 5 reports estimates of the proportional hazard model of job separation in equation 8. The dependent variable is the length of job tenure, including both current (censored) job spells and completed jobs spells for which a separation is recorded. The explanatory variables are the level of earnings at the start of the job, and annualized earnings growth from the start until the end of the job. The results are complementary to the findings on within-job earnings growth reported in Table 4. There is strong evidence that workers who receive a higher quality job match are less likely to exit, and weaker evidence that high rates of within-job earnings growth have a similar effect. As discussed in the previous section, this negative dependence of job separations on earnings and earnings growth will contribute to an upward bias in the cross-sectional estimates of β_2. Furthermore, inasmuch as earnings growth enters significantly in this equation, differenced estimates of β_2 will be similarly biased as the returns to tenure for those who stay in their job are significantly higher than for those who exit.

Table 5: Modelling Job Duration - Hazard Rates

	Pooled		Self-Emp		Wage	
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln w_{ij,t=0}$	-.254	-.304	-.426	-.464	-.366	-.418
	(.085)***	(.089)***	(.146)***	(.154)***	(.118)***	(.122)***
$\Delta_1 \ln w_{ijt}$		-.316		-.269		-.306
		(.187)*		(.325)		(.231)
Obs.	495	495	223	223	272	272

The dependent variable is job tenure, either at the time of separation. On the right hand side, $\ln w_{ij(t=s)}$ is the individual earnings at the start of the job. In contrast, $\Delta \ln w_{ijt}$ is the change in the log earnings from the start of the job until the end/date of interview. For current jobs the duration is censored at the time of interview. Estimates reported are hazard ratios. Coefficients greater (less) than 1 indicate that the variable in question increases (reduces) the probability that the job will end in any given period.

6 Conclusions

In this paper we have reviewed the cross-section evidence for one country, Ghana, as to how earnings, for both the self-employed and wage earners, are related to experience and job tenure. In Ghana as in many other countries in sub-Saharan Africa self-employment has expanded far faster than wage employment. It is important to know both how earnings growth compare across these two activities and what is the source of the age and tenure earnings profiles.

Taken literally, the age and tenure-earnings profiles which we and others have documented in cross-sectional data could be interpreted to suggest that poverty is, on average, a transitory phenomenon from the individual's perspective. In Ghana the earnings of a young person aged 20 rose, in the early 1990s, from about US$25 per month to US$35 by age 40 in both wage and self-employment, an increase of nearly 40 per cent. Cross-section estimates of the return on twenty years of tenure yield increases in excess of 60 per cent for both types of employment. Thus it appears from the cross-section that earnings can more than double during the first twenty years of working and this is true for both wage and self-employment.

We have extended work on cross-sections by using a panel data set that allows the possible sources of this rise of earnings with age and tenure to be investigated. The cross-section estimate of the return on age and tenure may be biased for several reasons. Clearly age is not a direct measure of work experience. From our panel we can construct measures of work experience based on actual periods in the labour force. We have focused on two possible biases in the cross-section estimate of the return on tenure. The first is that the quality of the job match may vary across jobs. The second is that there may be heterogeneity in the returns to tenure across individuals in the sample for which we can observe earnings and tenure increases.

If the primary source of the increases of earnings with age and tenure is general and specific learning in the classic Becker (1964) sense of the term we would expect that time spent in the labour force would be a better measure of work experience than age. We would also expect to be able to show that earnings growth within jobs was similar to that from the cross-section.

Our evidence from the panel is preliminary and open to alternative interpretations. We find that measured time in the labour force is less well correlated with earnings than age, suggesting that age is related to factors other than general learning. We have also presented evidence that at least part of the return to tenure observed in the data (for both wage employees and the self-employed) may be due to selection bias. Workers who remain in a given job receive substantial returns to tenure - more than 10% per annum among the self-employed. However, it is not clear that workers who move jobs could have achieved similar earnings gains if they had accumulated more tenure. Prior to exiting, 'movers' report per annum earnings growth of approximately 4% in self-employment. For wage employees the returns to tenure for 'stayers' are indistinguishable from zero, while for 'movers' they were approximately *negative* 11%.

These findings have significant implications for our understanding of the sources of rising lifetime incomes in developing economies. The size of the selectivity bias we have documented suggests that the cross-sectional tenure-earnings profile may dramatically misrepresent the earnings growth available to an average worker. While we have compelling evidence that the cross-section results are misleading as to the lifetime earnings profile the sources of the bias remain to be firmly established. Both movement based on job match quality and heterogeneity in the return to tenure in the job may play some part.

While we have focused on selection problems in the tenure coefficient, a similar bias may exist in the experience- and age-earnings relationships. We know from the GLSS data that older workers are more likely to be in the rural area. This may reflect a migration process by which relatively young workers migrate to the urban sector and relatively unsuccessful older workers migrate back to the rural sector. Such a pattern of migration would produce a return from age and work experience for the self-employed which would reflect learning about ability rather than the more traditional interpretation of an age earning profile as reflecting general work experience. At present this explanation remain to be tested.

While much work remains to be done to test these preliminary findings we note that in all the regression reported so far there is no evidence at all that earnings rises for the self-employed are lower than in wage employment. If the sources of the rising earnings profiles can be more firmly established it will inform our understanding of the lifetime earnings opportunities of those now entering labour markets in Africa increasingly dominated by self-employment, rather than wage, opportunities

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Appendix: Data Underlying Figures ?? & 1

Table A-6: Wage & Non-Wage Employment in Ghana

	1987/88		1988/89		1991/92		1998/99	
All	%	000s	%	000s	%	000s	%	000s
Wage Employees	17.3	1,121	18.1	1,215	15.4	1,143	13.2	1,166
Government	8	518	7.9	530	7.8	579	5.9	521
State Ent.	1.9	123	2.3	154	1.2	89	0.6	53
Private	7.4	480	7.9	530	6.4	475	6.7	592
Self-employment	19.5	1,264	24.2	1,624	23.5	1,744	27.3	2,411
Unpaid Family	2.2	143	1.1	74	1.3	96	0.3	26
Agriculture	58.7	3,804	54.6	3,664	56.7	4,207	55.7	4,918
Unemployed	2.2	143	1.9	127	3.2	237	3.5	309
Total Lab. Force	100	6,480	100	6,710	100	7,420	100	8,830
Urban								
Wage Employees	33.8	727	34	739	30.6	725	23.6	681
Government	13.9	299	14.3	311	15.2	360	10	289
State Ent.	3.7	80	4.3	93	2	47	1.1	32
Private	16.2	348	15.4	335	13.4	318	12.5	360
Self-employment	36.3	781	42.1	915	42.6	1,010	48.1	1,389
Unpaid Family	4.1	88	1.8	39	2	47	1.7	49
Agriculture	21	452	17.7	384	16.7	395	18.7	540
Unemployed	4.8	103	4.5	97	8.2	193	7.9	228
Urban Lab. Force	100	2,151	100	2,174	100	2,370	100	2,887

Source: GLSS Surveys and author calculations.

Table A-7: Urban Incomes & Human Capital in Ghana

	Monthly Earnings in 1998 Cedis	Monthly Earnings in US$	Years of Education	Age	Tenure in Years
Female					
Median	90,665	34	4	35	4
Mean	215,506	80	4.8	36.7	7.5
Std	836,287	312	4.8	12.2	8.7
N	1618	1618	1618	1618	1618
Male					
Median	135,716	50	10	37	7
Mean	251,717	94	7.7	38.9	9.8
Std	519,514	199	5.1	13.1	9.9
N	1090	1090	1090	1090	1090
Total					
Median	110,239	40	8	35	5
Mean	230,081	85	6	37.6	8.5
Std	725,712	272	5.1	12.6	9.3
N	2708	2708	2708	2708	2708

Includes wage and non-wage incomes. Based on GLSS 1 - 3, covering years 1987/88, 1988/89, and 1991/92.

Table A-8: Earnings Equations in GLSS

	Self Employed	Wage Employees	All
	(1)	(2)	(3)
Male	0.483	0.179	0.397
	(7.95) **	(2.56) *	(8.08) **
Education	-0.042	-0.021	-0.031
	(2.93) **	(1.30)	(2.93) **
Education^2/100	0.567	0.409	0.488
	(5.29) **	(4.53) **	(7.23) **
Age	0.041	0.039	0.042
	(3.04) **	(2.02) *	(3.53) **
Age^2/100	-0.055	-0.037	-0.052
	(3.45) **	(1.61)	(3.65) **
Tenure	0.038	0.053	0.04
	(5.09) **	(5.34) **	(6.39) **
Tenure^2/100	-0.058	-0.133	-0.07
	(2.90) **	(4.21) **	(3.95) **
Waged			-0.354
			(7.61) **
Constant	11.469	10.074	11.409
	(41.22) **	(25.25) **	(48.06) **
Observations	2004	704	2708
R-squared	0.15	0.23	0.15