DETERMINANTS OF INCOME IN INFORMAL SELF-EMPLOYMENT: NEW EVIDENCE FROM A LONG AFRICAN PANEL*

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Abstract

This article investigates the returns to workers' productive assets, in the form of physical capital, human capital and labour, in an African labour market. We specify a model for the income-generating process grounded in the literature on firms' production technology, hence abridging the gap between the analysis of individual earnings and the study of firms' value added. Identification in the empirics is achieved by means of panel estimators that are suitable to address the endogeneity of input choices, which derives from both time-varying and time-invariant unobservable heterogeneity. The use of these estimators is made feasible by the length of a newly constructed Ghanaian household panel dataset at CSAE. We further explore issues of endogeneity in the selection of different technologies, defined by their capital and labour-intensity. Finally, we analyse the *shape* of returns to capital, with the aim to detect potential non-convexities in technology. The results evidence that capital and work-experience play the strongest role in income-generation, while the shares of value-added attributed to labour and to formal schooling are low. Marginal returns to investment are high at low capital levels, but they decrease very rapidly, pointing against the existence of non-convexities due to minimum-scale requirements and implying that real income gains resulting from micro-investment are modest.

JEL Codes: J24, J31, O12, O17

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*This paper uses data from the six rounds of the Ghana Urban Household Panel Survey, conducted by the Centre for the Study of African Economies (CSAE). The dataset forms part of ongoing CSAE research into urban African labour markets funded by the ESRC, RECOUP, IDRC, DFID and the Gates Foundation. We are greatly indebted to Moses Awoonor-Williams and members of the Ghana Statistical Office, who assisted in the data collection.

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1 Introduction

SELF-EMPLOYMENT REMAINS THE PREDOMINANT TYPE OF OCCUPATION in may developing countries, where the number of self-employed workers, mainly in the informal economy, has often been rising in recent decades. (see Kingdon et al. (2006)). A positive view of this phenomenon would say that the progressive relaxation of credit constraints has allowed an increasing number of workers to reap the benefits from profitable investment opportunities. A negative view, on the other hand, would argue that a growing informal economy resulted from the failure to create a sufficiently large industrial sector that could provide workers with desirable wage-opportunities. The central empirical issue in assessing these alternative views is the consistent estimation of the returns to workers' *productive assets*: *physical capital, labour and human capital* in self-employment. Can we successfully model the income generating process in informal self-employment and can we successfully measure the oucomes of interest in a context of widespread lack of numeracy and literacy skills? Are returns to productive assets high enough to support the optimists' argument? And how do these returns compare to the returns to the same assets in alternative occupations (e.g. wage-employment)? These are some of the questions we will attempt to answer in this article. Moreover, we take a step further and attempt an analysis of the *shape* of the returns to capital over the range of capital stocks observed, with the aim to assess whether there exist any *non-convexities* in the production technology that may justify the existence of poverty traps at low capital levels.

The first challenge we face is trying to model the income generating process in informal self-employment and, in doing so, trying to abridge the gap between the analysis of individual workers' earnings and the study of firms' production. After presenting our model and our identification strategy, we will estimate returns to physical, human capital and labour in self-employment using a newly collected 'long' panel dataset from urban Ghana, gathered by the Centre for the Study of African Economies. The survey was conducted between 2004 and 2009 at yearly intervals and is now sufficiently long to allow the use of complex panel estimators that will enable us to purge our estimates from both time-invariant and time-variant sources of endogeneity in factors of production. Given the computational intensity of these methodologies and the scarcity of long panels in the African context, the results in this paper constitute an important contribution to the discussion on returns to productive assets in African labour markets.

Our results show that physical capital and labour market experience play the strongest role in the income generating process for the self-employed. The share of value-added attributed to labour is considerably smaller and, most strikingly, formal education does not play a role in enhancing the productivity of the self-employed in the informal economy. We conclude that learning on the job is a significantly more important dimension of human capital than formal schooling. When we control for the endogenous choice of capital intensive production technologies using a first stage selection model, we find that our core results do not change significantly. Although we identify a number of strong predictors for the choice of technology (gender and marital status among the most prominent ones), the estimated returns to productive assets remain largely unchanged. Finally, when we explore the shape of the production function over the range of capital observed, we find a *highly concave* technology. Marginal returns to investment are high at very low capital levels (it is not uncommon to find businesses that operate with capital value equal to 10 (real) USD), but they dicrease as rapidly. The implication of these results are two-fold. On the one hand, coupled with evidence of low entry costs, this result points against the existence of non-convexities in the production technology driven by minimum-scale requirements. On the other hand, the real income gains that result from high marginal returns are modest as they are produced from very low capital stocks. Therefore, whether high marginal returns to investment will translate into firm-growth (as firms re-invest their profits and attempt to *bootstrap* themselves out of poverty) remains open to debate, as it will partly depend on the workers' inter-temporal preferences.

The paper is structured as follows. In section 2 we outline our model of the income generating process. In section 3 we describe the dataset and discuss our choice of measures of the capital stock, which will be central to the analysis. In section 4, we outline our results and discuss their potential interpretations. In Section 5 we test the robustness of our results agains the possibility of endogeneity in the choice of the production technology. Section 6 explores the shape of the production function in greater detail, searching for potential evidence of non-convexities in the production set. Section 7 concludes.

2 Identification of the income-generating technology

Let the income of a self-employed worker be governed by the following process, based on a standard Cobb-Douglas production function. Our choice of the model comes from the view that despite the small size of the enterprises in our sample (often reducing to a single worker), earnings in self-employment ought to be investigated using the analytical tools generally deployed to study firms' output (production functions), rather than individual earnings (earnings regressions). Like larger formal firms, one-worker enterprises generate 'value-added', transforming raw-materials into final products via a multi-factor technology. Crucially, in addition to capital and labour, this technology will be augmented by the human capital of the entrepreneur (education and labour market experience), whose effects are important to draw conclusions on the returns to a worker from choosing self-employment (presumably as an alternative to potential wage-opportunities).

$$Y_{it} = A(H_{it}, X_{it}, u_{it}) K_{it}^{\alpha} L_{it}^{\beta} \tag{1}$$

where Y_{it} denotes the output of firm i at time t, measuerd as 'value added'[1], K_i is the stock of physical capital, L_i denotes units of labour (measured as total hours of work, including the entrepreneur's), A_i captures firm's productivity, which we assume is a function of the entrepreneur's stock of human capital (H_{it}) (proxied by the number of years spent in formal education), labour market experience (proxied by age) and other individual characteristics such as gender (included in X_{it}). u_{it} is an unobserved component of productivity, which can be further de-composed into

$$u_{it} = \gamma_0 + \delta_t + \eta_i + \omega_{it} \tag{2}$$

where γ_0 denotes average productivity across firms, δ_t captures period specific effects that are common across firms, η_i is a time-invariant firm-specific fixed effect

[1] This choice follows the most common approaches in the literature (see Basu () and Eberhardt and Helmers ())

and ω_{it} contains shocks to productivity that are period and firm-specific. Log-linearisation transforms the above production technology into the following empirical analog:[2]

$$y_{it} = \alpha k_{it} + \beta l_{it} + \gamma H_i + \theta X_{it} + (\gamma_0 + \delta_t + \eta_i + \omega_{it}) \tag{4}$$

where lower case letters denote log-values.

The estimation of (4) poses a number of challenges. First, the optimal choice of capital and labour by the firm is likely to depend on the unobservable components of productivity. In fact, it could easily be shown that the marginal product of capital and labour are a function of these unobservables. Hence, depending on the speed at which inputs can be adjusted, we can expect that they will be either (a) a function of the time-invariant heterogeneity (η_i) only or (b) a function of both time-variant and time-invariant heterogeneity (δ_t, η_i, ω_{it}). As it is well-known, under either of these circumstances, OLS estimates will be biased, as either of the following assumptions may not hold:

$$E[k_{it}u_{it}] = 0; \quad E[l_{it}u_{it}] = 0 \tag{OLS}$$

Our identification strategy will first control for individual fixed effects by means of within group transformations (WG) and differencing (DIFF), which are both feasible given the panel structure of the data. However, even the less restrictive identifying assumptions necessary for WG and DIFF estimation to be unbiased may fail to hold if time-varying heterogeneity plays a role in the choice of inputs. As in reality there appears to be sufficient flexibility in that choice, we believe this is a legitimate concern.

$$E[k_{it}(\delta_t + \omega_{it})] = 0; \quad E[l_{it}(\delta_t + \omega_{it})] = 0 \tag{WG/DIFF}$$

[2]This specification implicitly assumes:

$$A(H_{it}, X_{it,} u_{it}) = e^{\gamma H_i + \theta X_{it} + (\gamma_0 + \delta_t + \eta_i + \omega_{it})} \tag{3}$$

Time-dependent shocks (δ_t), which are common across firms, will be controlled for by means of time-dummies. The only remaining source of time-varying unobserved variation will therefore be ω_{it}, which will take center stage in the remainder of the identification stragegy.

Before outlining the details of how we will tackle endogeneity caused by time-invariant unobservables, however, the second main challenge posed by the above estimation comes from the fact that the optimal level of human capital accumulation chosen by the individual may depend on his/her unobserved productivity. For instance, more productive (able) individuals may also have lower costs of school attendance and therefore acquire higher levels of capital. Since human capital is time-invariant in our analysis (workers accumulate formal education in their youth and once they enter the labour market, that capital stock remains fixed; and we do not allow for depreciation in human capital), the only unobservables in (4) that may affect the optimal choice of H_i is η_i. Panel techniques such as Differencing and WG transformations are not suitable in their simplest form to deal with this problem, as they will not enable us to estimate the effect of education which is itself time-invariant. To remedy this problem, we will employ the Blundell and Bond (1998) System-GMM estimator, as well as complementary Instrumental Variable techniques using external instruments (such as distance from schooling during childhood) to ascertain the true returns to schooling.

Our identification strategy to deal with time-invariant unobservables constitutes the most challenging part of the analysis. Exploiting the length of our panel, we base our procedure on a series of estimators, which have been extensively used in the literature on the empirical estimation of production functions: Anderson and Hsiao (1982), Holtz-Eakin et al. (1988), Arellano and Bond (Difference GMM) Arellano and Bond (1991) and Blundell and Bond (1998) (System GMM). A more detailed discussion of the estimation techniques is provided in the appendix.

In the absence of reliable *external* instruments for input choices, the estimators listed above provide a framework to use lags of the endogenous variables as instruments, after applying the first-difference transformation that controls for time-invariant heterogeneity. Making different identifying assumptions allows us to use different lag-lengths as instruments. Namely, one option is to assume that inputs are *pre-determined*, in the sense that input choice is affected by past, but not current productivity shocks.

$$E[k_{is}\omega_{it}] = 0; \quad E[l_{is}\omega_{it}] = 0 \quad \forall \ t \geq s \tag{GMM1}$$

Alternatively, one can assume that input choices are *endogenous*, in the sense that they are affected by both past and current productivity shocks.

$$E[k_{is}\omega_{it}] = 0; \quad E[l_{is}\omega_{it}] = 0 \quad \forall \ t > s \tag{GMM2}$$

In our subsequent analysis, we will first assume pre-determinedness of K and L and then relax the former assumption, allowing Labour, which is generally believed to be more flexibly adjusted in the absence of formal contracts, to become endogenous. We maintain that due to the likely presence of credit-constraints in the economy, capital stocks are less flexibly adjusted, which justifies maintaining the pre-determinedness assumption.

3 Data

We estimate the production model using data from the Ghana Household Urban Panel Survey ('GHUPS'), conducted by the Centre for the Study of African Economies (CSAE) at the University of Oxford. The survey was launched in 2004 and it now spans 6 years, an unusual length for panel data-sets in developing countries. The GUHPS covers four cities: Accra, Kumasi, Takoradi and Cape Coast. Respondents were drawn by stratified random sampling of urban households from the Population and Housing Census of 2000. The survey was designed to cover all household members of working age at the time of the interview. After the first wave, the sample expanded by incorporating new members of the original households, as well as new households formed by individuals who had left their original household and were tracked to their new locations.

The GUHPS contains a wide range of workers' characteristics and, most importantly, a wide range of work-related variables, such as business size, location and, crucially, capital data. It is important to underline that the GUHPS overcomes important measurement issues, which have often raised scepticism about the possibility of measuring the earnings and, more generally, the business characteristics of informal self-employed workers with any degree of precision. These concerns are not unreasonable, given that informal businesses often lack written book-keeping and are run by workers with poor literacy and numeracy, who may find it hard to produce the figures they are asked to provide. Thanks to intensive enumerator training and to the use of portable computers (PDAs) in the data collection, it was possible to perform a number of *live* consistency checks during the interviews, which increased precision.

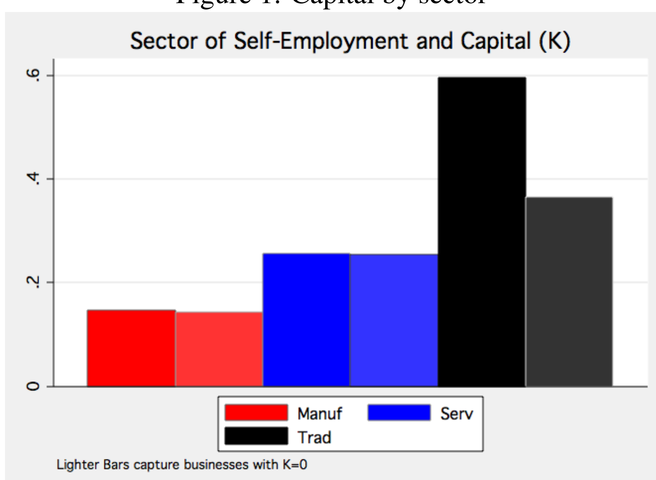
Table 1: Summary Statistics - Income per month and Value of Capital - 1997USD

Variable	**Mean**	**Median**	**N**
Value Added	135.21	71.36	1304
Profit	129.79	66.58	1304
K	212.98	27.09	1304
R	809.33	102.67	1304
K+R	1022.29	230.83	1304
$K > 0$	0.76		1304

3.1 Labour, Human Capital and Physical Capital

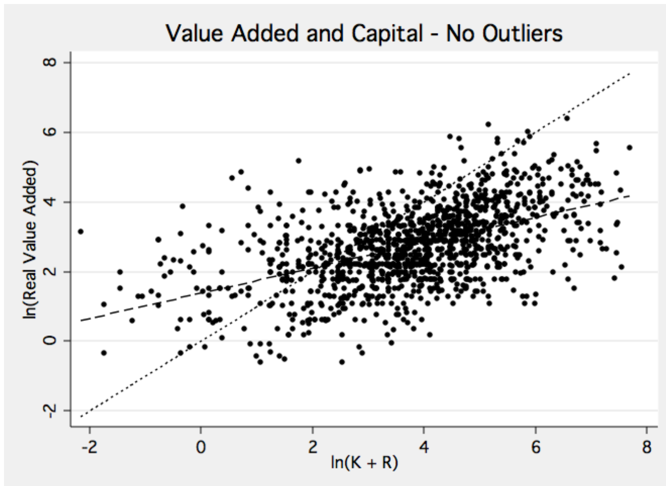
Given the central role that workers' productive assets play in the analysis, we should briefly discuss how these are measured. Labour enters the production function in the form of *total hours* of work employed in the business. This includes both the hours worked by the entrepreneur/business owner and the hours worked by any hired labourers. The latter, however, is not observed in the data. To overcome this limitation, we generate total hours of hired labour as the product of total number of hired labourers times 40 hours per week, which we think constitutes a valid approximation. Human capital is constituted by the workers' number of *years in formal education*, which is directly observed in the data, and by his/her *labour market experience* (proxied by age). The measure of physical capital we observe in the data is the *total value of tools and equipment* employed in the business. Interestingly, this is reported to be 0 for about 25% of the sample (see Table 1) and, almost exclusively, by traders (see figure 1). Reflecting upon the nature of micro trading businesses, such as the unprocessed-food sellers who are one of the most common categories in our sample, this feature of the data does not seem implausible. Such workers are unlikely to require any capital stock for their income-generating technology, other than the *merchandise* they buy and re-sell. It results, therefore, that limiting our analysis to one of capital stocks in the strict sense of tools/equipment/machinery used in production, would overlook an important part of the picture. Our approach, therefore, is to construct our capital measure as the sum of total value of tools and equipment (K) and of working capital (R) - the amount of money invested in business merchandise and raw-materials. This approach is further supported by the empirical observation that respondents who borrow for their businesses (e.g. from microfinance institutions) largely do so in order to finance the purchase of merchandise.

Figure 1: Capital by sector



As figure 2 shows, there appears to be a clear and stable relationship between the (real) value of capital (K+ R) and earnings. In estimating the production model outlined above, we will test the strength of this relationship in a multivariate setting that attempts to control for the endogeneity in input choice.

Figure 2: Capital and Value Added



4 Results

The results from estimating the production function (4) are reported in Table 2. First, our estimates show a strong and statistically significant effect of physical capital on value added. In line with our priors, a simple OLS regression delivers an upward-biased coefficient, presumably the result of unobserved ability or productivity shocks driving the choice of capital by the entrepreneur. Once individual fixed effects are controlled for (WG), the bias is significantly reduced (the coefficient drops from .27 to .20), but not entirely eliminated. Indeed, instrumenting the first-differences using lagged values of K and L (under the initial assumption that they are bot pre-determined with respect to time-invariant unobservables), we find that the coefficient drops further, albeit marginally.

We should remark that the Arellano-Bond GMM results (in the last column of table 2) are robust to concerns of serial correlation in the error terms (the AR(2) test results shows that we can reject the null of serial correlation) and pass the Hansen Test of overidentifying restrictions. It is well-known that the validity of this test has been subject to severe criticism in contexts where the use of lags leads to proliferation of instruments (Roodman (2009a,b)). Unfortunately, the literature does not offer a clearcut rule to judge whether an instrument set is too large, except for the intuitive rule of thumb that when the instrument set approaches N, the model is invalid (Roodman (2009a). As reported at the bottom of table 2, the instrument set we use comprises 22 instruments. We believe, therefore, that with a dataset of over 400 observations, our instrument set is 'safely' small.

The results on the role of labour in the production technology are less clearcut. The OLS coefficient is .20, while the WG coefficient is .11. Instrumenting using lags, we are unable to pin down an estimate with sufficient precision. A discussion of how the labour variable is constructed may help clarify this result. In our estimation, labour is the sum of the hours worked by the entrepreneur and by his/her employees. The latter, however, is obtained by multiplying the number of employees by a standard number of weekly hours of work (set at 40), since the actual number of labour hours is not observed. It follows that identification of the coefficient on L is achieved through variation in the number of hours worked by the entrepreneur and by the number of employees working in the business. Given that the large majority of workers in our sample does not employ any additional labour (other than themselves) and the number of hours worked per week does not display strong variation, the degree of variation in the data may be insufficient for precise identification. This concern is particularly strong given that our panel estimators crucially achieve identification through within-firm variation over time, which is unlikely to be strong. However, despite lack of precision in the GMM regressions, the OLS and WG results suggest that returns to labour in micro-enterprises are considerably lower than returns to capital. Given the nature of the businesses that prevail in the Ghanaian urban economy, capital, and in particular working capital, constitute the most valuable productive asset. Small trading businesses (e.g. food and clothes sellers) are indeed unlikely to benefit considerably from hiring labour, since, with the exception of the cost of transportation (which may be sporadic or outsourced to the suppliers), there would appear to be no 'processing task' that labour could be useful for. In fact, most frequently, the task of selling the goods is effectively fulfilled by the firm owner on his/her own (especially if the business is in a fixed location, like a market stall, where the entrepreneur can easily supervise its operations) and we can hypothesise that until a certain scale is reached (e.g. a formal shop, which would be rarely observed in our sample), the marginal product of additional labour will be close to 0.

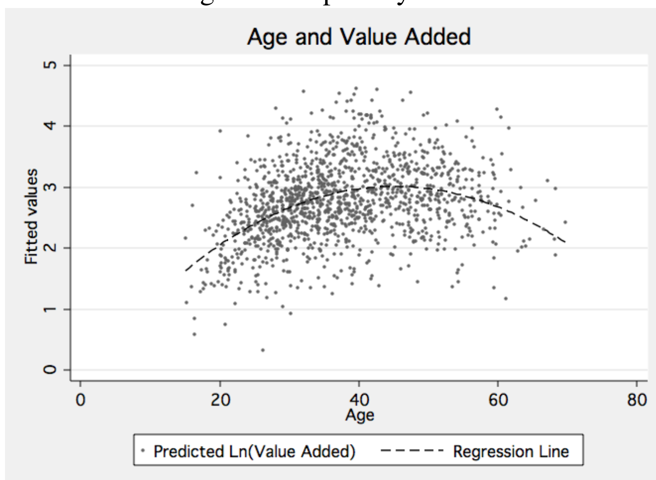
Turning to Human Capital, the results show a clear and strong effect of labour market experience (proxied by age). The OLS regressions show a highly concave age-earnings profile. After transforming the data to account for fixed-effects, we are no longer able to identify the linear effect of age separately from the average time-effect common across people (since age is assumed to change by exactly 1 for all the individuals in the sample), but we are still able to pick up the concavity of the effect. Figure 3 plots the age-earning profile implied by our OLS regression. Perhaps more interestingly, our OLS results show no significant relationship between formal education and the earnings of the self-employed. This result tells us that in an economy where the informal sector is quickly expanding and absorbs an increasing share of the population, formal education has not provided workers with the skills they require to increase their productivity.[3] Such finding would seem to corroborate the hypothesis that education acts primarily as a signal in the Ghanaian labour market, allowing people to access desirable employment opportunities in the formal economy (e.g. public sector), while it does not add much to their productivity in the informal economy. An alternative explanation may be that formal education provides the *wrong* set of skills, which are not applicable in informal self-employment.

When we interact productive assets with gender, we find that a larger proportion of value added is attributed to capital among women than among men, while the opposite is true for labour. Labour market experience and education, on the other hand, do not appear to have significantly different coefficients among men and women. While potentially suggestive of a number of different hypotheses, these results are confined to the OLS estimation in the current draft and hence remain mainly descriptive.

Finally, despite the imprecision in the labour coefficient, our estimates appear to indicate overall *decreasing returns to scale* with respect to capital and labour, a finding that deserves some discussion. The direct implication of decreasing returns to scale is that if the business attempted to expand, the resulting increase in value added would be less than proportional. This finding may appear counter-intuitive,

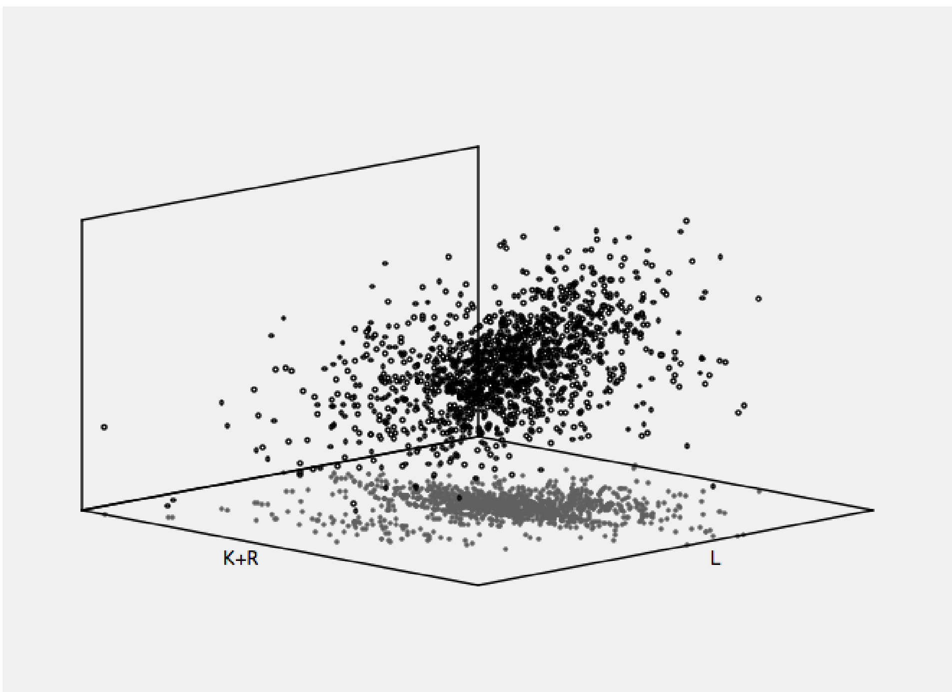
[3]This result will deserve more attention in subsequent drafts of the paper, when we will employ System-GMM and external instruments to identify the education coefficient

Figure 3: Capital by sector



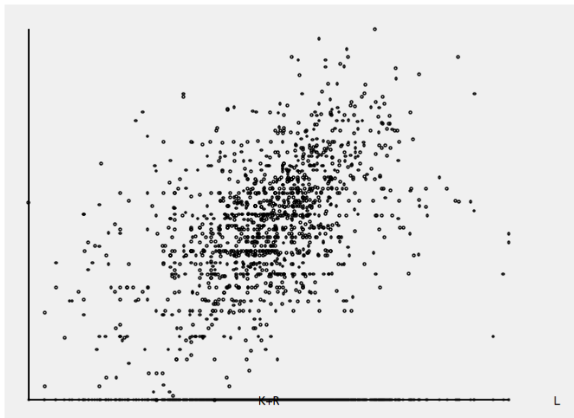
given the high marginal returns to capital we estimated, unless we hypothesise the existence of additional factors of production that may not be captured by our regressions and are implicitly held constant when performing simple comparative statics (examples would include buildings and other structures, such as market stalls). This hypothesis is corroborated by the fact that, as in most published studies of production technologies, a large share of variation in our regressions is idyiosinchrstic and unexplained by our model (R2 in OLS is about .3). To the extent that such factors are correlated with capital and labour, however, we would expect an upward bias in the estimated coefficient, the sum of which is instead found to be rather low (mainly due to the very low returns to labour). Most plausibly, given the nature of the businesses that prevail in the Ghanaian economy (small trading enterprises), an important role will be played by *location* and *information*; especially if these are the factors that crucially allow traders to gain from arbitrage of unprocessed goods across markets (e.g. whole-sale to retail, countryside to city). Knowledge of this kind would traditionally be labeled as TFP in standard production analyses. However, whether information should feature more explicitly among the factors of production in a sample dominated by traders, remains an interesting possibility.

Figure 4: Income, Capital and Labour



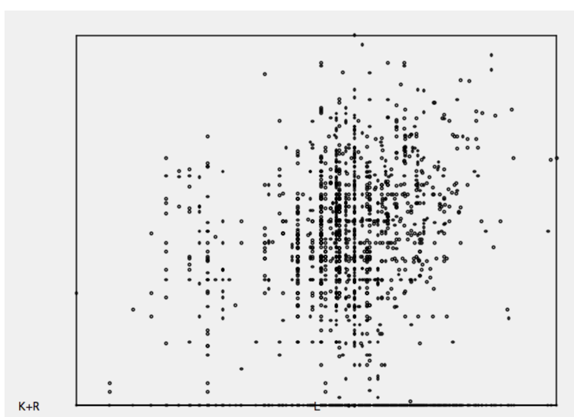
NOTE: The chart is a 3-D plot of log-value-added (on the vertical axis) against the log value $K + R$ and log number of hours (L) (on the horizontal axes).

Figure 5: Income and Capital



NOTE: The chart plot of log-value-added (on the vertical axis) against the log value of $K + R$ (on the horizontal axis).

Figure 6: Income and Labour



NOTE: The chart plot of log-value-added (on the vertical axis) against the log number of hours (L) (on the horizontal axis).

Table 2: Determinants of value-added in informal self-employment

	OLS	OLS2	OLSINT	WG	FD	AH	HNR	DIFF-2S
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
K+R	.272	.272	.341	.196	.183	.147	.171	.180
	(.017)***	(.017)***	(.021)***	(.026)***	(.028)***	(.061)**	(.051)***	(.063)***
L	.197	.197	.127	.108	.059	.083	.077	.004
	(.038)***	(.038)***	(.044)***	(.051)**	(.054)	(.117)	(.095)	(.093)
Educ	.002	.010	.005		-.011			
	(.007)	(.021)	(.008)		(.011)			
Educ2		-.0007						
		(.002)						
Age	.074	.074	.077		-.008			
	(.016)***	(.016)***	(.019)***		(.012)			
Age2	-.0008	-.0008	-.0008	-.002	.002	-.001	-.001	-.0009
	(.0002)***	(.0002)***	(.0002)***	(.001)**	(.005)	(.002)	(.002)	(.001)
Male	.504	.506	.831		.148			
	(.060)***	(.061)***	(.705)		(.097)			
(K+R)*Male			-.111					
			(.035)***					
L*Male			.138					
			(.084)*					
Educ*Male			-.024					
			(.016)					
Age*Male			-.004					
			(.033)					
Age2*Male			-.0002					
			(.0004)					
2007	.222	.222	.179	.464	.339	.466	.448	.419
	(.076)***	(.076)***	(.075)**	(.109)***	(.093)***	(.153)***	(.150)***	(.142)***
2008	.130	.129	.108	.627	.201	.497	.480	.438
	(.073)*	(.073)*	(.072)	(.188)***	(.073)***	(.300)*	(.299)	(.242)*
2009	-.090	-.091	-.138	.717		.463	.434	.386
	(.070)	(.070)	(.069)**	(.283)**		(.468)	(.465)	(.388)
Const.	-.799	-.812	-1.092	4.980	.262			
	(.330)**	(.332)**	(.395)***	(1.545)***	(.197)			
Obs.	1304	1304	1298	1304	459	459	459	459
R^2	.313	.314	.346	.165	.171	.	.	
e(ar2p)								.022
e(hansenp)								.759
e(j)								22

***Confidence:* *** ↔ 99%, ** ↔ 95%, * ↔ 90%.**; DIFF-2S uses 2-step difference GMM with optimal weighting allowing for arbitrary patterns of heteroskedasticity and Widnmeijer (2005) small sample correction for se;

4.1 Returns to Capital

Using the results of our estimation and given the shape of the production function, we can compute marginal rates of return on capital at current levels of output and of the capital stock for all the firms in our sample.

$$\frac{\partial Y}{\partial (K+R)} = \alpha A(K+R)^{(\alpha-1)}L^{\beta} = \alpha \frac{Y}{(K+R)} \tag{5}$$

Table 6 summarises the distribution of these estimated returns *per month*, together with the distribution of the output/capital ratio (Y/K). Figure 8 plots the same marginal returns ($\partial Y/\partial(K+R)$) against capital ($K+R$). The plot shows the strong concavity of the production technology. Marginal returns to capital are very high at micro-investment levels, but, most strikingly, they decrease very rapidly over the range of capital we observe. The implication of this finding are at least two-fold. On the one hand, high marginal returns to micro-investments indicate that saving and re-investing business profits may be a viable growth opportunity, allowing small entrepreneurs to *bootstrap* their way out of poverty (McKenzie and Woodruff (2006)). This conclusion is reinforced by the empirical observation that entry-level capital stocks and start-up costs are minimal. On the other hand, however, when we translate the high marginal returns into real income gains (obtained by multiplying the marginal rate of return by the value of the capital stocks), the results appear to be modest. Graph 7 shows the distribution of marginal *real income gains* corresponding to the estimated marginal returns to investment. When we plot these real income gains against capital, the evidence becomes even more compelling (see figure 9). Despite decreasing marginal returns to capital, real income gains from investment *increase* steadily over the range of capital (after excluding extreme values, see part (b)) and at the median value of the capital stock (approx 190USD), the real income gain is less than 15USD per month. Despite substantial in relative terms, therefore, income gains resulting from investment are rather low in absolute terms, a finding that begs the question of whether profits of such magnitude are in fact re-invested and not consumed, in an economy where a substantial segment of the population lives below the poverty line. Answering this question would partly rely on being able to test workers time-preferences (i.e. discount rates).

Table 3: Distribution of *Output/Capital* and *Returns to Capital*

	1st	**5th**	**25th**	**50th**	**75th**	**95th**	**99th**
$\frac{ValAdd}{(K+R)}$	.01	.04	.15	.31	.74	4.31	20.8
$\frac{\partial ValAdd}{\partial(K+R)}$	.001	.006	.02	.05	.12	.72	3.49

NOTE: Returns to Capital computed using 2-Step Difference-GMM estimate of $\alpha = .168$

Figure 7: Returns to Capital as real income gains

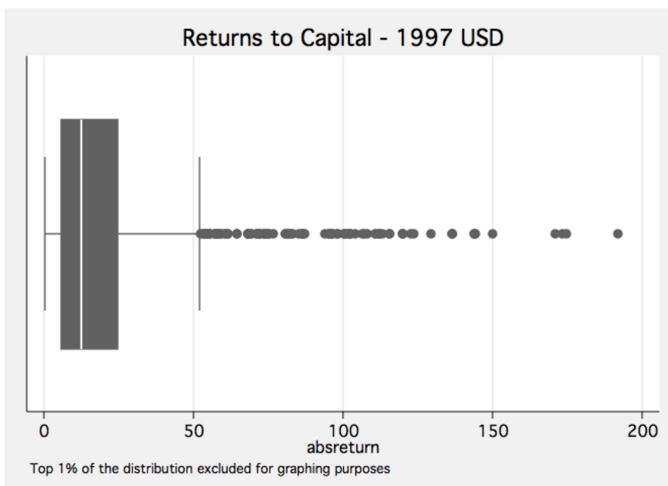
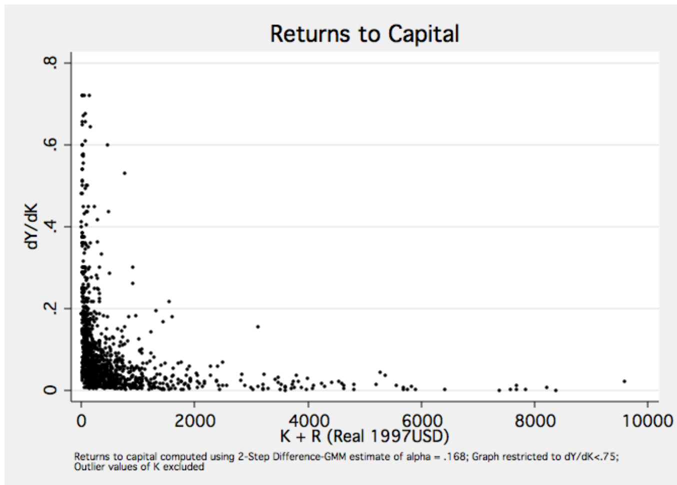


Figure 8: Marginal Returns to Capital



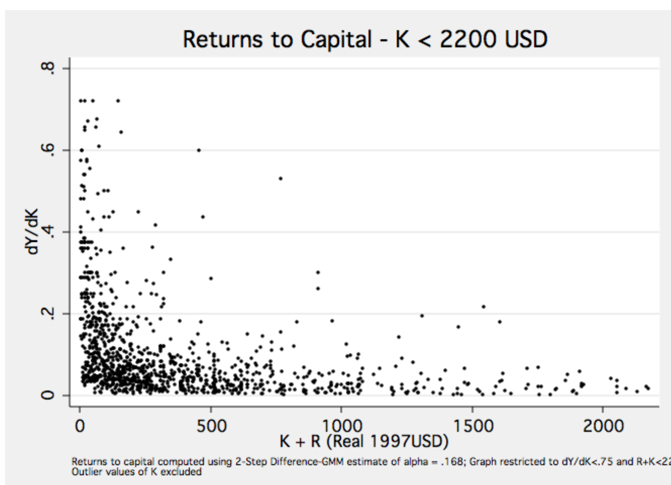
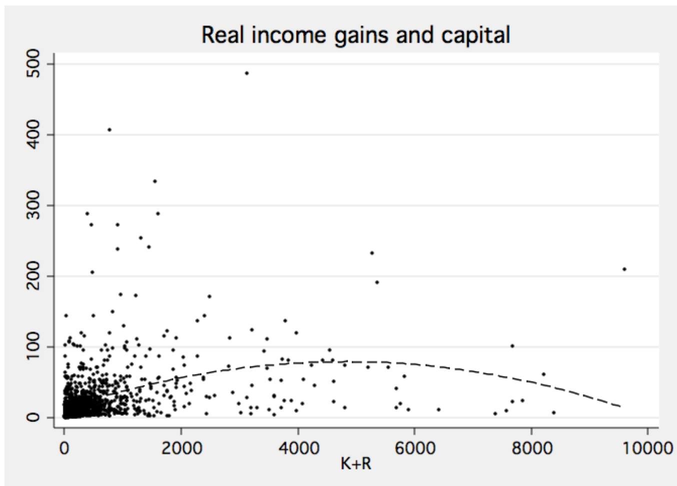
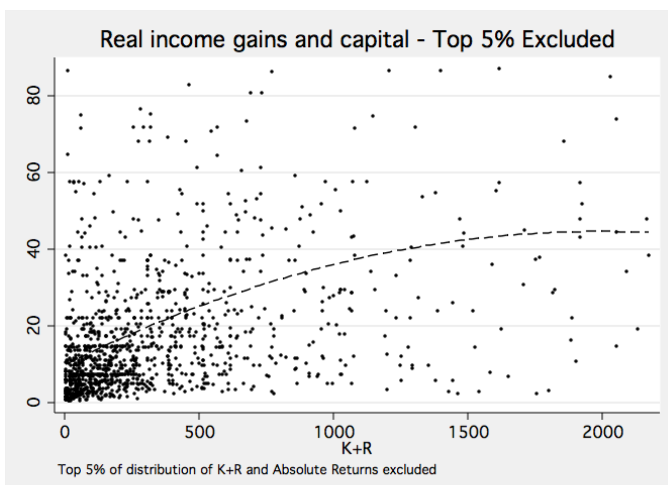


Figure 9: Real income gains and Capital





5 Endogenous production technology

Our identification strategy so far has abstracted from a potentially important dimension of endogeneity: *discrete choices in the production technology*. It was documented in the previous section that a considerable share of workers (about 25% of the sample) produce with K = 0 and R > 0 (i.e. their only capital in production are the raw materials they employ). As figure 1 showed, these workers are almost exclusively traders. By lumping all capital into a single variable, our approach so far has effectively imposed uniformity on the effects of K and R on value added, and in doing so we have effectively mitigated the selection problem that would occur in a logarithmic production function that used K and R separately (where observations with K = 0 would drop out of the analysis). In this section, we want to explore this dimension of selection in greater detail. This part of the analysis should not be read as an alternative to the previous instrumental variable approach, but rather as a complement, adding more robustness to the treatment of endogeneity by tackling it from a different angle.

Our approach proceeds in two steps. In section 5.1, we estimate our production function separately for people with $K = 0$ and $K > 0$, using a selection model à la Heckman (1979), in a two-stage procedure where the first stage controls for selection into what we call a *capital-intensive technology* $(K > 0)$. In section 5.2, we recognise that an additional important dimension of *discrete* variation in the production technology is the choice of whether to employ (or not) labour *in addition* to the entrepreneur's own time. We devise, therefore, a first stage selection model where the choice is among four different technology choices, defined by combinations of zero/positive levels of K and hired labour ($L = 0$ / $L > 1$). This econometric framework is based on the selection-correction model developed by Dubin and McFadden (1984) and further developed by Bourguignon et al. (2004). We then control for this multinomial choice in the second stage, with an interest to determine whether endogenous technology selection biases our results. Crucially, both models hinge upon the existence of valid exclusion restrictions that yield valid instruments for selection in the first stage (discussed below).

5.1 Heckman Selection: K>0

We augment our model of production by the following selection equation:

$$D_{K>0,i,t} = 1(Z_{it}\delta + v_{it} \geq 0) \tag{6}$$

where $D_{K>0,i,t} = 1$ if we observe $K > 0$ and zero otherwise, Z_{it} is a vector of variables which comprises X_{it} plus additional instruments for selection and v_{it} is an error term assumed to be independent of Z_{it}. A standard assumption, which we will make, is that Z_{it} is exogenous in (4), such that

$$E(u_{it}|X_{it}, Z_{it}) = 0 \tag{7}$$

If this assumption holds, it follows that

$$\begin{aligned}
E[y_{it}|D_{Z>0,it} = 1] &= E[y_{it}|v_{it} > -Z_{it}\delta] \\
&= \alpha k_{it} + \beta l_{it} + \gamma H_i + \theta X_{it} + E(u_{it}|v_{it} > -z_{it}\delta) &(8)\\
&= \alpha k_{it} + \beta l_{it} + \gamma H_i + \theta X_{it} + \rho E(v_{it}|v_{it} > -z_{it}\delta) &(9)\\
&= \alpha k_{it} + \beta l_{it} + \gamma H_i + \theta X_{it} + \rho\lambda(z_{it}\delta) &(10)
\end{aligned}$$

where we assume joint normality of u_{it} and v_{it} to move from (8) to (9) and λ is the inverse Mills ratio when $D_{K>0,i} = 1$. From the normality assumptions it results that $D_{K>0,i}$ given Z follows a probit model such that:

$$Pr(D_{K>0,it} = 1) = \Phi(Z_{it}\delta) \tag{11}$$

which can be used to derive the mills ratio to be included in our principal equation as a control for selection.

Estimating this model on the entire sample will allow us to estimate $\hat{\delta}$ and compute individual values of the inverse Mills ratio $\hat{\lambda}_{it} = \lambda(Z_{it}\hat{\delta})$, which we can include in the earnings model on the selected sample to correct for the bias. Our estimates of $(\alpha, \beta, \gamma, \theta)$ will now be consistent. This procedure will also provide us with a simple tool to test for the presence of selection bias. Namely, if the coefficent on $\hat{\lambda}$ in the selection-corrected model (ρ) is not significantly different from 0, we will conclude that sample selection is not a major cause of concern for our results. Clearly, such conclusions will hinge upon the validity of the model assumptions. The results of the second stage estimation are reported in Table 4, while the first stage results of the selection model are reported in table 5.

The instruments for selection we use in the first stage are a workers' *marital status* and *unexpected expenses or losses of income/assets* over the year prior to the interview. The rationale for the former instrument is that marriage may contribute to relaxing credit constraints by giving workers access to the assets of their spouse's family and to a new support network, without necessarily affecting his/her productivity. The first part of the intuition seems to be confirmed by the first-stage results in the empirical appendix (table 5), where marriage appears to significantly increase the probability of working in a capital-intensive business. The main problem with this instrument consists of the potential endogeneity of marriage, with respect to prior wealth. Hence, we introduce the latter two instruments, which we believe constitute a more robust engine of exogenous variation in the selection equation. Our first-stage model results confirm that workers who faced an unexpected loss of assets/income (due to damages to their property, theft, perished inventories, etc.), are less likely to be producing with a capital intensive technology $K > 0$ in the current period. The result is in line with the hypothesis that negative shocks deplete workers' capital. Being the result of unexpected events, such shocks can be held to be exogenous in the earnings equation. The limitation with the use of this variable is due to the fact that it was not recorded in 2007, and therefore we are forced to drop a year of data when using them.

The results of the second stage estimation are reported in table 4. They show that the consequences of controlling for selection are minimal. There is evidence of slight (positive) bias in the returns to capital due to endogenous selection of the technology. In fact, the insignificant coefficient on λ tells us that selection is not playing a strong role in the equation. And even when the coefficient is significant at the 15% level (HECK 4), the results do not change considerably. [4]

[4] A further source of improvement on this approach will be to estimate the model via Full-Information Maximum Likelihood that re-estimates the first and second stage equation jointly and therefore

Table 4: Determinants of value-added - *Endogenous Technology*

	OLS	HECK1	HECK2	HECK3	HECK4
	(1)	(2)	(3)	(4)	(5)
K+R	.257 (.019)***	.258 (.019)***	.254 (.021)***	.239 (.022)***	.239 (.022)***
L	.189 (.044)***	.190 (.043)***	.207 (.049)***	.176 (.052)***	.175 (.052)***
Educ	-.013 (.037)	-.022 (.040)	-.043 (.046)	-.040 (.055)	-.039 (.056)
Educ2	-.002 (.002)	-.001 (.002)	-.0004 (.002)	-.0007 (.003)	-.0008 (.003)
Age	.048 (.020)**	.067 (.029)**	.066 (.033)**	.078 (.033)**	.080 (.033)**
Age2	-.0005 (.0002)**	-.0008 (.0004)**	-.0008 (.0004)**	-.001 (.0004)**	-.001 (.0004)**
Educ*Age	.0008 (.0007)	.0009 (.0007)	.0009 (.0009)	.0007 (.001)	.0006 (.001)
Male	.498 (.067)***	.557 (.095)***	.548 (.122)***	.561 (.118)***	.570 (.119)***
2007	.221 (.087)**	.247 (.095)***			
2008	.178 (.085)**	.212 (.096)**	.226 (.105)**	.203 (.108)*	.208 (.110)*
2009	-.132 (.079)*	.022 (.182)	.085 (.235)	.115 (.213)	.137 (.211)
Const.	-.146 (.469)	-.767 (.814)	-.820 (1.026)	-.897 (1.003)	-.981 (.995)
$\hat{\lambda}$		.601 (.631)	.828 (.848)	.988 (.736)	1.075 (.722)
Obs.	996	1410	1126	1000	1000
e(N-cens)		414	323	288	288
R^2	.302				

Confidence: ***** ↔ 99%, ** ↔ 95%, * ↔ 90%**.; Robust standard errors in parentheses

makes more efficient use of the available information. The advantage, though, comes at the cost of stricter assumptions on the joint distribution of the error terms.

Table 5: Endogenous choice of capital-intensive technology (First Stage)

	HECK1	HECK2	HECK3	HECK4
	(1)	(2)	(3)	(4)
Educ	-.022 (.043)	.007 (.048)	.041 (.053)	.039 (.053)
Educ2	.0004 (.002)	-.0003 (.003)	-.003 (.003)	-.003 (.003)
Age	.044 (.022)**	.038 (.025)	.041 (.028)	.040 (.028)
Age2	-.0007 (.0003)***	-.0005 (.0003)*	-.0005 (.0003)	-.0005 (.0003)
Educ*Age	.00008 (.0008)	-.0005 (.0009)	-.0006 (.0009)	-.0006 (.0009)
Male	.215 (.083)***	.230 (.093)**	.217 (.099)**	.218 (.099)**
2007	.083 (.098)			
2008	.117 (.097)	.117 (.096)	.083 (.104)	.090 (.105)
2009	.560 (.100)***	.560 (.100)***	.562 (.107)***	.562 (.107)***
Married	.209 (.075)***	.181 (.085)**	.168 (.091)*	.169 (.091)*
Finan.Loss			-.209 (.119)*	-.180 (.127)
Unexp.Exp.				-.061 (.092)
Const.	-.319 (.486)	-.325 (.550)	-.390 (.601)	-.348 (.605)
Obs.	1410	1126	1000	1000

***Confidence:* *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%**.; Robust standard errors in parentheses

5.2 Multinomial Selection

In this section we refine our analysis of the potential endogeneity in the choice of the production technology. We do so by constructing a multinomial first-stage selection model, whereby workers sort into one of four types of production technology.

Table 6: Multinomial Production Technologies

	$L = 1$	$L > 1$
$K = 0$	TECH 1	TECH 2
$K > 0$	TECH 3	TECH 4

In addition to whether or not the firm uses positive values of K, we now model the selection into using hired labour (in addition to the entrepreneur's own labour, $L > 1$). Indeed, as most of our sample is constituted of firms with $L = 1$, we are especially interested to analyse the endogeneity of becoming an 'employer' (against remaining a one-worker firm). If labour-intensive technologies are chosen for endogenous reasons, explicitly modeling the process of selection should add robustness to our analysis. Our choice of analysing the discrete variation between L=1 and L>1 is driven, like in the case of capital, by the hypothesis that labour is itself lumpy and characterised by important indivisibilities.

The first stage selection model is now based on a multinomial logit model of the probability of being in one of the four technologies above. The results are reported in table 7. In a first attempt to estimate the model (reported in this version of the paper), we choose to focus on marital status as the only instrument for the choice of technology. In fact, given the computational intensity of this methodology, the reduction in sample size caused by using the additional instruments may render the estimation unfeasible (though additional instruments will clearly deserve more attention as we expand this section of the analysis). Quite strikingly, the results in table 7 show a strong effect of marriage on the allocation into different technologies. Not only marriage seems to relax credit constraints, but it also presumably relaxes constraints on the amount of labour that can be hired in the business, as the spouse and his/her family members are now likely to participate in production (see TECH4 in table 7).

In the second stage we re-estimate the income model, controlling for selection by means of the selection terms generated from the first stage estimates (see Dubin and McFadden (1984)). A feasible methodology to implement this estimator was designed by Bourguignon et al. (2004), to whom the reader is referred for a detailed explanation of the estimation approach. The results of the second stage estimation are reported in table 8, where we choose to focus on Technology 3 and 4, which are the ones that employ positive levels of K and therefore lend themselves to direct comparison with the results of the Hackman model in the previous section. As a benchmark, we report the OLS results re-estimated on the selected samples. Controlling for selection produces only slight differences in our estimates. We find evidence of a slight positive bias in the estimated coefficients, but, again, we are unable to draw strong conclusions on whether selection matters statistically, as the coefficient on the selection correction terms in the second stage (m1 - m3) are statistically insignificant.

Table 7: Multinomial Choice of Technology - *MLOGIT - (FIRST STAGE)*

	TECH2	TECH3	TECH4
Educ	.012 (.039)	-.023 (.020)	.023 (.024)
Age	.073 (.084)	.022 (.044)	.003 (.053)
Age2	-.0005 (.001)	-.0005 (.0005)	-1.00e-05 (.0006)
Male	1.219 (.332)***	.766 (.196)***	1.119 (.221)***
2007	1.267 (.387)***	.414 (.220)*	1.526 (.266)***
2008	.766 (.385)**	.265 (.197)	1.164 (.250)***
2009	.137 (.511)	.934 (.213)***	1.854 (.259)***
Married	-.205 (.304)	.296 (.156)*	.652 (.192)***
Const.	-4.428 (1.736)**	-4.428 (1.736)**	-4.428 (1.736)**
Obs.	1310	1310	1310

***Confidence:* *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%**.; Base Category: TECH 1; Outliers dropped

Table 8: Determinants of value-added - *Multinomial Choice of Technology*

	OLS - T3	DMF - T3	OLS - T4	DMF - T4
K + R	.272 (.022)***	.270 (.022)***	.229 (.038)***	.240 (.039)***
L	.079 (.062)	.069 (.062)	.468 (.135)***	.479 (.135)***
Educ	-.007 (.009)	-.045 (.017)***	.003 (.016)	-.062 (.085)
Age	.071 (.021)***	.097 (.025)***	.032 (.039)	.124 (.099)
Age2	-.001 (.001)***	-.001 (.0004)***	-.0002 (.0005)	-.002 (.002)
Male	.594 (.079)***	.783 (.294)***	.214 (.129)*	.007 (.022)***
2007	.271 (.104)*	-.051 (.371)	.035 (.182)	-.666 (1.250)
2008	.191 (.098)*	-.068 (.254)	.060 (.184)	-.479 (1.012)
2009	-.173 (.091)	-.179 (.254)	-.140 (.171)	-.027 (.810)
m1		-1.359 (1.395)		-.746 (4.002)
m2		.852 (1.599)		-4.119 (3.431)
m3		-1.254 (.59)**		4.907 (4.907)
Const.	-.215 (.459)	-1.876 (1.034)**	-1.064 (.985)	1.230 (5.112)
Obs.	706	706	283	283

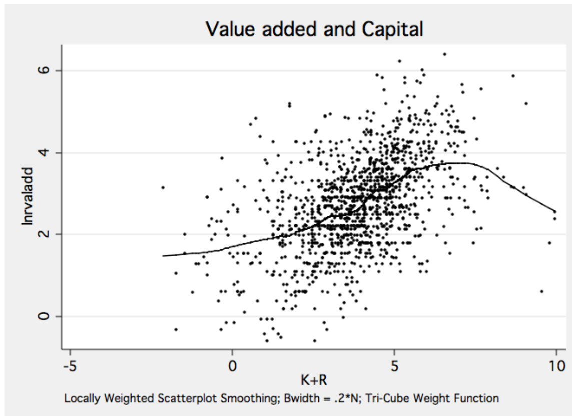
Confidence: ***** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%**.; Base Category: TECH 1; OLS-T3 and OLS-T4 report Ordinary Least Squares estimates confined to the samples of workers using technology 3 and 4 respectively; DMF-T3 and DMF-T4 report selection-corrected estimates using the Dubin-McFadden (1984) methodology to model selection into technology 3 and 4 respectively;

6 Non-convexities in production

Our empirical model, derived from a log-linearisation of a Cobb-Douglas production function, has so far imposed a linear relationship between log-capital and log-earnings. In this section we relax that assumption and allow for greater flexibility in the shape of the function. Our point of departure figure 10, where we plot a locally weighted scatterplot smoothing of earnings against capital (K + R). The graph is suggestive of the hypothesis that returns to capital might be lower both at the low and at the top end of the capital distribution. This is an intriguing descriptive fact, as it points to the plausible existence of non-convexities in the production set. Non-convex production sets may result from minimum-scale entry requirements in production, lumpy investment and convex production technologies. As discussed in a large literature on poverty traps, the existence of such non-convexities may forestall the development process, as if it hinders growth at low levels of capital. Banerjee and Newman (1993) develop a model to describe how capital constraints that induce people into non-capital intensive occupations may lead the economy to a low-growth equilibrium. McKenzie and Woodruff (2006) discuss the role of non-convexities in production, while finding no evidence for them in their data. In particular, they explain how the co-existence of production non-convexities and poorly functioning capital markets may lead to poverty traps, as workers are unable to *borrow* nor *bootstrap* (via savings) their way out of poverty. In the absence of non-convexities, even with poorly functioning capital markets, poverty traps may cease to exist.

In order to explore the evidence further, we first re-estimate our production technology on each tertile of the capital distribution separately, with a view to assess differences in the magnitude of the estimated effects. The results are reported in table 9, and they evidence some interesting patterns. In businesses with medium levels of capital, the production technology is closer to one with constant returns to scale, and labour plays a much stronger role in production. It would seem, therefore, that only the most capital intensive businesses in our sample are characterised by strongly decreasing returns. A potential explanation for this finding is that higher income is associated with higher measurement error in the data (effectively, heteroskedasticity), and therefore, our precision in identifying the effects of

Figure 10: Marginal Returns to Capital



the factors of production drops. This hypothesis is supported by the drop in the R^2 in the last two columns of table 9.

Next, we refine the analysis by allowing greater flexibility in the estimator. Figure 11 shows the results from estimating fractional polynomial regressions that select the best fitting equation out of a number of non-linear alternatives of the following kind:

$$y_{it} = \sum_{m=1}^{M} \alpha_m k_{it}^{p_m} + \beta l_{it} + \gamma H_i + \theta X_{it} + (\gamma_0 + \delta_t + \eta_i + \omega_{it}) \qquad (12)$$

where each power p_m is chosen from a restricted set.[5]. All combinations of powers are fitted to the data and the best fitting model is obtained.

Despite its purely descriptive value, this exercise shows that even after we allow for greater flexibility in the relationship between capital and income, we are far from detecting regions of non-convexity in the relationship between capital and income, *ceteris paribus*. Coupled with evidence of extremely small start-up costs reported by the entrepreneurs in our sample, these findings show that production is feasible at very low levels of the capital stock, where it yields the highest re-

[5]The algorithm we choose searches over the following powers of p_m: -2, -1, -.5, 0, .5, 1, 2, 3

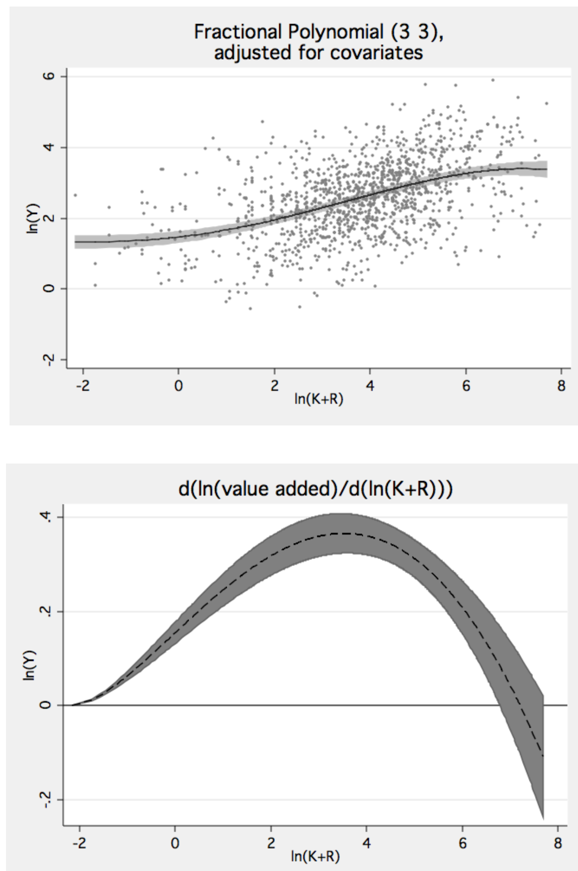
Table 9: Income by (K+R)-tertile

	OLSQ1	WGQ1	OLSQ2	WGQ2	OLSQ3	WGQ3
	(1)	(2)	(3)	(4)	(5)	(6)
K+R	.21 (.05)***	.11 (.08)	.53 (.11)***	.50 (.18)***	.09 (.05)*	.04 (.09)
L	.26 (.06)***	.0002 (.11)	.22 (.06)***	.14 (.10)	.13 (.07)*	-.16 (.13)
Educ	.003 (.01)		-.01 (.01)		.01 (.01)	
Age	.09 (.02)***	1.05 (.81)	.04 (.03)	.36 (.65)	.09 (.04)**	.57 (1.18)
Age2	-.001 (.0003)***	-.0004 (.002)	-.0004 (.0003)	-.004 (.002)**	-.001 (.0004)**	-.004 (.003)
Male	.78 (.11)***		.44 (.10)***		.35 (.10)***	
2007	.24 (.14)*	-.61 (.73)	-.14 (.12)	-.16 (.60)	.43 (.14)***	.47 (1.12)
2008	.19 (.13)	-1.82 (1.64)	-.09 (.11)	-.19 (1.33)	.29 (.14)**	.03 (2.50)
2009	-.08 (.13)	-3.18 (2.57)	-.15 (.10)	-.24 (2.10)	-.02 (.13)	-.19 (3.91)
Const.	-1.34 (.49)***	-34.38 (27.87)	-1.04 (.70)	-6.60 (22.97)	.24 (.80)	-12.66 (44.96)
Obs.	419	419	445	445	440	440
R^2	.23	.08	.15	.17	.1	.14

***Confidence:* *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%**.; The constant term in the WG estiamtor is set-up to be the average of the fixed effects;

turns. This result runs counter to the hypothesised existence of poverty traps due to minimum investment requirements and credit constraints and is in line with the evidence obtained by McKenzie and Woodruff (2006).

Figure 11: Fractional Polynomial Estimation



7 Conclusions

This article has investigated the returns to workers' productive assets in an African labour market. From a theoretical standpoint, we have argued a case for abridging the existing gap between the analysis of individual earnings and the study of firms' value-added, using a model of the income-generating process that is grounded in the study of enterprises' production functions. From an empirical perspective, we have attempted identification of the objects of interest by means of a 'long' african panel dataset, collected by CSAE from 2004 to 2009. The panel dimension of the data has allowed us to employ panel estimators that are suitable to address concerns of endogeneity in input selection due to both time-varying and time-invariant unobservables.

The results we obtain evidence that physical capital and labour market experience play the strongest role in the income generating process of the self-employed. The share of value-added attributed to labour is considerably smaller and, most strikingly, the productivity-enhancing effect of formal education in self-employment is negligibly small. We conclude that learning on the job is a significantly more important dimension of human capital than formal schooling. When we control for the endogenous choice of capital intensive production technologies using a first stage selection model, we find that our core results do not change significantly. Although we identify a number of strong predictors for the choice of technology (gender and marital status among the most prominent), the estimated returns to productive assets remain largely unchanged. Finally, when we explore the shape of the production function over the range of capital observed, we find a highly concave technology. Marginal returns to investment are high at very low capital levels (it is not uncommon to find businesses that operate with capital value equal to 10USD), but they decrease as rapidly. The implication of this result are two-fold. On the one hand, coupled with evidence of low entry costs, these findings point against the existence of non-convexities in the production technology driven by minimum-scale requirements or regions of convex technology. On the other hand, the real income gains that result from high marginal returns are modest as they are produced from very small capital stocks. Whether high returns to investment will be conducive to firm growth as firms re-invest their profits and attempt to *bootstrap* themselves out of poverty remains therefore open to debate, as it will partly depend on the workers' inter-temporal preferences. Studying the growth of these firms using the panel dimension of our data will be the aim of future research.

A robust assessment of returns to micro-entrepreneurship indirectly allows us to shed light on the effectiveness of policies aimed at relaxing workers' credit constraints in developing countries. In particular, the proliferation of micro-credit as a povery alleviation tool is grounded in the belief that profitable investment opportunities are available to the poor, but cannot be taken advantage of, due to the existence of bindning credit constraints. The proliferation of microcredit schemes in Ghana over the last few decades supports this argument. Our results show that this view is apparently justified by the existence of high marginal returns to capital at very low capital stocks (similar in magnitude to the capital-stocks at which micro-finance operates). However, we remain sceptic on the effectiveness of micro-investments as a poverty-alleviation strategy, since the size of the real income gains resulting from such investments is very small and the lack of functioning saving markets coupled with potentially low propensity to save among the poor, may constitute the missing link in a poverty alleviation strategy. Ultimately, whether these micro-enterprises grow out of their initial microscopic size is an empirical research question that we are going to investigate next, exploiting our panel dataset further. Finally, our assessment of the returns to human capital in self-employment and of the potential complementarities between physical and human capital in small-scale informal production, which we find to be weak, has informed us of the limited effectiveness of universal education policies in economies where the majority of available earning opportunities appear to be in informal self-employment. It would appear that while education may be granting workers access to desirable wage-opportunities (e.g. the public sector), it fails to enhance their productivity in informal self-employment.

A APPENDIX

A.1 Robustness to outliers

Table 10: Value Added - Hours - No Outliers

	OLS	WG	AH	HNR	DIFF-2S
	(1)	(2)	(3)	(4)	(5)
K+R	.311 (.018)***	.249 (.029)***	.153 (.061)**	.164 (.052)***	.179 (.061)***
L	.184 (.037)***	.115 (.050)**	.089 (.117)	.090 (.094)	.017 (.094)
Educ	.0009 (.007)				
Age	.073 (.015)***				
Age2	-.0008 (.0002)***	-.002 (.001)**	-.002 (.002)	-.002 (.002)	-.001 (.001)
Male	.477 (.060)***				
2007	.199 (.075)***	.402 (.110)***	.503 (.152)***	.496 (.150)***	.457 (.145)***
2008	.117 (.072)	.554 (.188)***	.584 (.301)*	.579 (.300)*	.530 (.247)**
2009	-.119 (.069)*	.621 (.282)**	.607 (.468)	.599 (.466)	.539 (.392)
Const.	-.827 (.326)**	4.499 (1.539)***			
Obs.	1281	1281	449	449	449
R^2	.335	.192	.	.	
e(ar2p)					.032
e(hansenp)					.74
e(j)					22

Confidence: ***** ↔ 99%, ** ↔ 95%, * ↔ 90%**.; DIFF-2S uses 2-step difference GMM with optimal weighting allowing for arbitrary patterns of heteroskedasticity and Widnmeijer (2005) small sample correction for se;

A.2 Relaxing pre-determinedness of labour

Table 11: Relaxing pre-determinedness of labour - Hours

	OLS	WG	AH	HNR	DIFF-2S
	(1)	(2)	(3)	(4)	(5)
K+R	.272	.196	.194	.172	.152
	(.017)***	(.026)***	(.122)	(.053)***	(.061)**
L	.197	.108	-1.080	-.030	.143
	(.038)***	(.051)**	(.935)	(.239)	(.217)
Educ	.002				
	(.007)				
Age	.074				
	(.016)***				
Age2	-.0008	-.002	.0007	-.0009	-.001
	(.0002)***	(.001)**	(.003)	(.002)	(.002)
Male	.504				
	(.060)***				
2007	.222	.464	.518	.453	.437
	(.076)***	(.109)***	(.266)*	(.151)***	(.143)***
2008	.130	.627	.399	.472	.460
	(.073)*	(.188)***	(.527)	(.301)	(.251)*
2009	-.090	.717	.083	.400	.452
	(.070)	(.283)**	(.862)	(.474)	(.403)
Const.	-.799	4.980			
	(.330)**	(1.545)***			
Obs.	1304	1304	334	459	459
R^2	.313	.165	.	.	
e(ar2p)					.028
e(hansenp)					.756
e(j)					19

***Confidence:* *** ↔ 99%, ** ↔ 95%, * ↔ 90%**.; DIFF-2S uses 2-step difference GMM with optimal weighting allowing for arbitrary patterns of heteroskedasticity and Widnmeijer (2005) small sample correction for se;

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