

Who Benefits from Promoting Small and Medium Scale Enterprises?

Some Empirical Evidence from Ethiopia

Bob Rijkers

Caterina Ruggeri Laderchi

Francis Teal

The World Bank
Africa Region
Poverty Reduction and Economic Management Department
May 2008



Abstract

The Addis Ababa Integrated Housing Development Program aims to tackle the housing shortage and unemployment that prevail in Addis Ababa by deploying and supporting small and medium scale enterprises to construct low-cost housing using technologies novel for Ethiopia. The motivation for such support is predicated on the view that small firms create more jobs per unit of investment by virtue of being more labor intensive and that the jobs so created are concentrated among the low-skilled and hence the poor. To assess whether the program has succeeded in biasing technology adoption in favor of labor and thereby contributed to poverty reduction, the impact of the program on technology

usage, labor intensity, and earnings is investigated using a unique matched workers-firms dataset, the Addis Ababa Construction Enterprise Survey. The data are representative of all registered construction firms in Addis and were collected specifically for the purpose of analyzing the impact of the program. The authors find that program firms do not adopt different technologies and are not more labor intensive than non-program firms. There is an earnings premium for program participants, who tend to be relatively well-educated, which is heterogeneous and highest for those at the bottom of the earnings distribution.

This paper—a product of the Poverty Reduction and Economic Management Department, Africa Region—is part of a larger effort in the department to support evidence based policy making. Policy Research Working Papers are also posted on the Web at <http://econ.worldbank.org>. The author may be contacted at cruggeriladerchi@worldbank.org.

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Who Benefits from Promoting Small and Medium Scale Enterprises? Some Empirical Evidence from Ethiopia

Bob Rijkers¹, Caterina Ruggeri Laderchi² and Francis Teal^{1*}

¹Centre for the Study of African Economies
Department of Economics
University of Oxford

²World Bank, Washington DC

We would like to thank the staff of the Ethiopian Economic Association, in particular Ato Kibre Moges, Ato Daniel Aklilu and Ato Assefa Adamassie and the supervisors and enumerators of the Addis Ababa Construction Enterprises Survey. Discussions with Dr Wubshet Berhanu, City Manager, Addis Ababa City Government, and Woz. Tsedale Mamo, Manager, Addis Ababa Housing Development Project Office and other staff at the Addis Ababa Housing Development Project Office have been most helpful to frame the analysis of this study. We also owe gratitude to Justin Sandefur at Oxford University as well as Emily Kallaur, Rumana Huque and Louise Fox at the World Bank. Seminar participants at a CSAE seminar at Oxford University, the CSAE conference on economic development and the IZA/World Bank conference on employment and development provided useful feedback. Bob Rijkers gratefully acknowledges financial support from the Prins Bernhard Cultuurfonds and the Herbert and Ilse Frankel Memorial Fund at Oriel College, Oxford. All errors are our own. The views expressed in this paper are those of the authors and do not necessarily reflect those of the World Bank, its Board of Executive Directors, or the countries they represent.

*Authors' names are in alphabetical order. Corresponding authors e-mail addresses: brijkers@worldbank.org and francis.teal@economics.ox.ac.uk

1. Introduction

Whether or not programs which promote small and medium scale (SME) enterprises can stimulate job creation and contribute to poverty reduction in developing countries is an important question. The motivation for such support is often predicated on the view that small firms create more jobs per unit of investment by virtue of being more labor intensive and that the jobs so created are concentrated among the low-skilled and hence the poor. In spite of the policy prominence of SME support programs, the empirical evidence for these propositions is weak. In a recent review of the literature Betcherman et al. (2004, p51) conclude:

The evaluation literature on the labor market impacts of ALMPs [Active Labor Market Programs] is thinnest in the case of micro-enterprise development and self-employment assistance programs. There are relatively few studies and of those that do exist, many are concerned with the program's effect on business development rather than on the future employment and earnings of participants.

The sparse available empirical evidence is entirely based on the experiences of developed and transition economies and suggests that micro-enterprise development programs typically have a positive impact on the employment prospects of participants, while their impact on earnings is mixed (see e.g. Fretwell et al, 1999, Tzannatos & Dar, 1999, and Betcherman et al. 2004).

This paper provides an analysis of the Addis Ababa Integrated Housing Program (AAIHDP) which is an active labor market program that attempts to tackle the severe housing shortages and high unemployment that prevail in Addis Ababa by deploying and supporting labor-intensive SMEs to construct low-cost condominium housing using technologies novel for Ethiopia. To assess whether the program has succeeded in biasing technology adoption in favor of labor and thereby contributed to poverty reduction, the impact of the program on technology usage, labor intensity and earnings of participants is investigated using a unique matched workers-firms dataset, the Addis Ababa Construction Enterprise Survey (AACES), which is representative of all registered construction firms in Addis, and was designed specifically for the purpose of analyzing the impact of the program.¹

The paper is organized as follows. The next section describes the program and its rationale. The data collected to analyze it is presented in section 3, which also presents descriptive statistics on the characteristics of program and non-program firms. In section 4 we assess the impact of the program on technology adoption. Section 5 describes the differences between program participants and non-participants and assesses the program's impact on earnings. A final section concludes.

2. The Addis Ababa Integrated Housing Program (AAIHDP)

By creating and supporting SMEs the AAIHDP aims to tackle simultaneously the problems of a housing shortage and unemployment. The specific objectives of the program include '*promotion of micro and small-scale enterprises, which can absorb more labor force and operate at a lower overhead cost*' as well as '*promotion of cost efficient housing construction technology*' (HDPO, 2004, p1). To achieve these objectives, the AAIHDP aims to construct 192,500 houses, generate 80,000 job opportunities, support 1,300 existing SMEs and create another 1,000 new ones.

To construct housing affordable by low-income dwellers, the IHDP designed a production process that deviates from the one conventionally used in the construction sector. The low-cost aspect of the program consists in building a less luxurious, homogeneous type of housing using novel low-cost construction technologies such as pre-cast beams and ribslabs, fixed-price contracts and standardized production procedures permitting greater specialization. To implement this production process, the IHDP intervenes in the construction sector by both creating new SMEs and providing support for firms in the program.

Participation in the program is conditional on passing a test. Anybody who has either

¹ This paper focuses on these aspects of SMEs and does not consider other possible benefits, such as their contributions to competition, entrepreneurship and innovation, creation of products which are more suitable for the poor as well as social and political dividends. See e.g. Biggs (2002) and Halberg (2001) for reviews of the empirical evidence regarding such benefits.

graduated from a Technical and Vocational Education and Training (TVET) college or can show proof of having experience in the construction sector can take a test to participate in the program. Successful candidates can establish an enterprise, either by themselves or together with other successful applicants. Individuals who failed the test are allowed to resit the test at a later date and may attempt to upgrade their skills by joining successful candidates in the project as apprentices.

Once firms are formed, they can register their interest in IHDP construction work with the Program Office, which is in charge of implementing the program. Existing firms are not allowed to compete for IHDP jobs unless IHDP capacity does not suffice. In theory, incumbent firms could attempt to join the program by having their employees take the test and regroup as a "new" firm. Anecdotal evidence suggests this is not very common. The IHDP does not create firms which can execute foundational and structural works but it does hire existing firms for these tasks. For the purposes of this paper, firms which can execute such tasks are referred to as contractors, while firms which cannot are referred to as constructors. The latter category consists predominantly of SMEs and is consequently of focal interest.²

The IHDP provides wide-ranging support to firms participating in the program by i) providing and, in certain cases, subsidizing a place to work, ii) facilitating access to credit, iii) providing training and access to inputs (on credit), iv) subsidizing machinery for firms producing rebars (reinforcement bars) or hollow blocks, v) providing training to firms engaging in pre-cast beam and hollow block production and vi) awarding contracts to program firms. Not all newly created SMEs are awarded contracts but IHDP contracts are almost exclusively awarded to firms created by the IHDP (except for contracts assigned to contractors).

By providing these different types of support the program alters the factor prices different firms face, which in turn affect technology adoption and factor choices and thus labor demand. The program does not affect technology adoption or factor usage directly. The modeling challenge is to identify the impact of the IHDP interventions on labor demand and earnings and separate the effect of the program from differences between participants and non-participants not due to participation.

At this juncture, it is important to note that the unit of analysis in this paper is the firm, not the house being constructed. Our data enable us to assess the impact of the program on the technology and labor intensity of constructors and contractors separately. The labor demand of the housing construction sector as a whole may also be affected by the mix between constructors and contractors in the construction process, if these firms differ in their labor intensity and/or adopt different technologies. Unfortunately, our data do not enable us to rigorously assess whether, and if so to what extent, such substitution effects are occurring.

3. The Addis Ababa Construction Enterprise Survey (AACES)

The AACES is a survey of matched firms and workers in the construction sector in Addis Ababa, designed specifically for the purpose of analyzing the employment creation impact of the IHDP World Bank (2007). It was conducted by the Ethiopian Economic Association in collaboration with the World Bank in December 2006 and early January 2007. It covered 240 firms and 971 workers, 241 of whom were casual workers. The workers' data contains detailed information on workers' earnings, their employment history, experience, skills, educational background, program participation, job satisfaction, motivation for choosing their current activity and on a number of socio-demographic characteristics including household characteristics and parental background.

The worker data will be considered in section 5, here we focus on the firm data. The sample of firms contains data on 103 non-program constructors, 92 program constructors, 17 non-program contractors and 28 program contractors. A program firm is defined as a firm which fulfils at least one of three criteria; i) having been created by the program ii) having received support from the program or iii) having worked for the program.³ The firm-level data provide information on a rich set of firm

² Conventionally, all firms with a contracting license grade - an indicator of technological capability - are referred to as contractors. Firms with a contracting license grade between 1 and 6 can execute foundational and structural works, while those with a license grade between 7 and 10 cannot. For expositional purposes we only refer to a subset of this group, namely those with a license grade between 1 and 6 as "contractors" in this paper.

³ In addition, there was one firm engaging in pre-cast beam production which did not meet any of these criteria

characteristics, including their activities, age, size, capital stock, inputs, outputs, expenditures, revenues, organizational and occupational structure, program participation and receipt of program support, access to finance and inputs, skilled personnel, constraints, expectations, their labor force and wages. In addition, the data contain information on the volume and total costs of inputs and outputs, enabling us to compute firm-specific input and output-prices, which provide natural instruments for factor choices.

Table 1 present descriptive statistics on program firms and non-program firms. On average, program firms employ more workers, have more capital, use more inputs and have a better educated workforce. In Graph 1, the amount of capital per worker is plotted against the size of the firm measured in terms of the number of employees. Capital intensity does not seem to differ between program and non-program firms and also does not vary systematically with firm-size, though contractors are significantly more capital intensive than constructors. These findings are backed up by regressions of capital intensity on firm-size (column 1), firm-size and program-participation (column 2), and firm-size, program-participation, and being a contractor (column 3) presented in Table 2. Neither the program dummy, nor the interactions of the program dummy with firm-size or being a contractor⁴ are significant, confirming that program firms are not more or less capital intensive than non-program firms. Moreover, the results do not suggest a relationship between firm-size and capital intensity. Contractors are significantly more capital-intensive than constructors, but the capital-intensity of contractors also does not vary with firm size.

Input-intensity does not seem to depend on program participation or on firm-size either, as illustrated by Graph 2, which plots input usage per worker against the number of workers. The graph does show that contractors seem to use more inputs per worker. Regressions presented in Table 3 reveal that input intensity is strongly correlated with capital-intensity and confirm that contractors use more input per worker, even after controlling for firm-size and capital intensity (see column 4). Size variables and program participation indeed have no impact, corroborating the intuition from the graphs.

4. Assessing Program Impact on Technology Adoption

4.1 A Cobb-Douglas Technology

To assess the impact of the IHDP on technology adoption and productivity a human capital augmented Cobb-Douglas production function is estimated; output, Y , is modeled as a function of physical capital, K , human capital, H , material inputs, M , and a technology parameter, A , using the familiar formula: $Y = AK^\alpha H^\beta M^\gamma$.⁵ Human capital, H , is assumed to be a function of the educational attainment of the workforce, E , and the number of workers L : $H = Le^{h(E)}$. This formulation enables us to control for both the quantity of labor, proxied by the number of workers, L , and the "quality" of labor, proxied by some function $h(E)$ of the average educational attainment of workers. Controlling for the skill level of workers is important since it will be shown that workers in program firms are on average better educated. Taking logs and imposing a linear functional form, i.e. $h(E) = \frac{\delta}{\beta} E$, yields an estimable equation of the human capital augmented production function:

but was classified as a program firm since the pre-cast beam technology is not widely applied by non-program firms as yet.

⁴ As a robustness check, controls for different activities were included, to analyse whether the composition of the sample could be driving the results. Controlling for activities did not overturn the result, nor did controlling for the interaction between activities and the size of the firms. Results omitted to conserve space, but available upon request

⁵ Our starting point for assessing technology differences was the more general translog production function. Since the translog specifications comfortably accepted Cobb-Douglas restrictions, we proceeded with Cobb-Douglas production functions. Results are omitted to conserve space, but available upon request.

$$\ln Y = \ln A + \alpha \ln K + \beta \ln L + \delta \ln E + \gamma \ln M + u$$

The "quality" of the labor force matters if $\delta \neq 0$. In our baseline specifications, however, δ is assumed to be zero (an assumption that is relaxed later).

To test whether program firms use a technology that differs from non-program firms, all the parameters of the production function are interacted with program participation, P .

$$\begin{aligned} \ln Y = & \ln A + \alpha \ln K + \beta \ln L + \delta \ln E + \gamma \ln M \\ & + \rho_A P^* \ln A + \rho_K P^* \ln K + \rho_L P^* \ln L + \rho_M P^* \ln M + e \end{aligned}$$

Under the null hypothesis of no differences in technology adoption, all interaction terms should be zero, both individually and jointly. The null hypothesis is rejected if at least one of them or any combination of them is significantly different from zero. This testing procedure is very general since we allow the program to impact on all parameters of the production function.

Table 4 presents the results of OLS estimation of the production function. The dependent variable is the log of annual revenue.⁶ The baseline explanatory variables are the factors of production and activity dummies. Information on one or more explanatory variables are missing for 70 firms, forcing us to reduce our sample to 170 observations. The specification presented in column 1 tests whether the technology used by contractors is different from that used by constructors. This is indeed the case; the dummy on being a contractor and the interaction term on being a contractor and capital are both strongly significant. Since the group of constructors is of focal interest and because the sample of contractors for whom production functions can be estimated is very small, we focus on constructors for the rest of this subsection.

The specification in column 2 tests for differences in technology between program constructors and non-program constructors. The null hypothesis that no such differences exist cannot be rejected since neither the program dummy nor the interaction terms of program participation with labor, capital and inputs are individually or jointly significant.

The specification in column 3 attempts to assess the impact of the heterogeneity of labor by including measures of the educational attainment and age of the workforce as additional explanatory variables. Neither enters significantly; the higher educational achievement of workers in program firms does not translate into higher productivity.

Overall, the basic Cobb-Douglas specifications fit the data rather well, as judged by the adjusted R^2 consistently exceeding 0.6. In addition, parameter estimates are consistent with Constant Returns to Scale for both program and non-program firms.

4.2 Tackling Endogeneity

It is well-known that OLS-estimates of the production function may be misleading when one or more of the explanatory variables are correlated with the error term, for example because of measurement error, simultaneous determination of inputs and outputs or omitted variable bias (see e.g. Akerberg,

⁶ Given the existence of a fixed price system, prices for products of program firms and non-program firms might differ, causing revenue to be a misleading indicator of productivity. We investigated this possibility by regressing price deflators on activity dummies and program participation but could not find evidence for systematic price differences between program and non-program firms. In addition, deflating revenue and inputs by output and input price deflators did not affect the overall pattern of results. Results omitted to conserve space, but available upon request.

2005). In addition to these conventional endogeneity concerns, we have to be on guard for selection bias, which arises when program participation is correlated with the error term, for example because there are unobserved factors not controlled for in the production function which are correlated with both productivity and the decision to participate.

Instrumental variables methods are used to deal with these endogeneity problems.⁷ To alleviate instrumenting requirements Constant Returns to Scale restrictions are imposed, enabling us to estimate output per worker as a function of the capital labor ratio and inputs per worker. To further facilitate identification, capital is assumed to be exogenous. The motivation for the latter assumption is that the capital stock is unlikely to change very much in the short run given high adjustment costs, while input usage is typically much more volatile. Given the severity of identification requirements, our strategy is to first assess the impact of the two types of endogeneity in isolation, before attempting to tackle their joint effect. An inputs price index is used as an instrument for inputs usage. Price is a theoretically appealing instrument since it is likely to affect output only through its impact on factor usage. Akerberg et al. (forthcoming) warn us, however, that orthogonality may nevertheless be violated when price differences are correlated with unobserved quality differences in both inputs and outputs. Program participation is instrumented using the size of the firm at startup, which we have shown to be strongly correlated with program participation. At startup, the firm has not yet benefited from IHDP support; size at startup is consequently exogenous under the fairly mild restriction that there is no direct link between initial size and productivity once current size is accounted for.

The results of our instrumenting regressions are presented in Table 5 and the corresponding first stage regressions are presented in Table A1 in the appendix. In column 1 endogeneity of inputs is the sole concern; program firms and non-program firms are pooled together and input usage is instrumented using the input price deflator, which is a good instrument as judged by the Cragg-Donald F statistic of 13.24. The resulting parameter estimate of the contribution of inputs to revenue is somewhat higher than the corresponding OLS estimate (presented in Table A2), yet the Hausman test comfortably accepts the null hypothesis of no endogeneity. This suggests that exogeneity of inputs is not a bad assumption, which is consistent with (statistically) random rationing of inputs in the presence of input constraints.

In columns 2 and 3 inputs- and capital per worker are assumed exogenous and selection bias is the key concern. To facilitate identification, column 2 models the impact of the program as a technology shifter. The results do not indicate that the program succeeds in increasing productivity; if anything, program firms are less productive. Moreover, IV estimates are lower than OLS estimates, suggesting upward, rather than downward selection bias. A possible explanation for such upward bias is that the program is capable of selecting the most able workers (amongst applicants). The specification in column 3 is more general as it also allows for an impact of the program on capital and inputs usage. The null hypothesis of no difference in technology cannot be rejected, though the parameter estimates are imprecise. Hausman tests comfortably accept the null of no exogeneity for both specifications, suggesting that the impact of selection bias is not large.

Columns 4 and 5 allow for the coexistence of selection bias and endogeneity of inputs usage. In column 4, the program impact is again modeled using a dummy, which is negative and insignificant. Column 5 adopts a more general specification. Parameter estimates are poorly behaved, probably because the predicted program participation and instrumented interactions are highly correlated. In addition, instruments are weak, as evidenced by the Cragg-Donald F score of 0.749. In short, the results of this estimation are disappointing. Nevertheless, the null hypothesis that the program has no impact on technology adoption is not rejected in either specification and Hausman tests do not reject the null hypothesis of exogeneity.

In conclusion, the finding that program firms do not use a different technology is unlikely to be driven by selection bias or endogeneity of factor inputs.

5. Assessing Program Impact on Earnings

Descriptive statistics, presented in Table 6, confirm that workers in program firms are on average

⁷ We also experimented with control function approaches. The results we obtained were similar to the results obtained using IV methods; they are omitted to conserve space, but available upon request.

better educated than workers in non-program firms. Table 7 presents probit models of the probability of being hired by a program firm. The first column is the baseline specification with age, gender, education and a dummy for having completed an apprenticeship as explanatory variables. Column 2 adds dummies for prior activities to this baseline specification to test whether program firms draw disproportionately on workers with an underprivileged labor market status. Column 3 adds dummies for workers' entire employment history and column 4 includes both employment history and prior activity dummies.

As to be expected, having a TVET degree is strongly positively associated with the probability of being employed in a program firm. The importance of training is further evidenced by the positive and significant coefficient on having completed an apprenticeship in the past, although this may also reflect the fact that those who do not pass the test can join the firm as apprentices. The insignificance of prior activity dummies reveals that program firms do not draw disproportionately on unemployed workers, casual workers and workers in otherwise marginal jobs. Focusing on the entire employment history of individuals instead demonstrates that workers who have experienced a significant unemployment spell (e.g. longer than three months) in the past, workers who have experience working in a cooperative, as well as workers who have experience as a domestic employee are significantly more likely to be employed in program firms, whereas workers who have experience as casual workers are less likely to be employed in program firms.

To model the impact of the program on wages, W , a standard earnings function approach is used. Wages are modeled as a function of observable characteristics, X , such as age, education and firm-characteristics, and the type of firm the worker is employed in, D_j . The potential endogeneity of participation and schooling are the two major obstacles to successfully estimating this earnings function. Selection bias arises when participants differ from non-participants in terms of unobserved characteristics that affect both earnings potential and the probability of being employed in a program firm, thus creating a correlation between the error term and the regressors and consequently causing the OLS estimator to be biased. To tackle this selection problem the Lee selection correction is used.⁸ The potential endogeneity of schooling, arising for example because of a correlation between schooling and ability, is also addressed by means of a control function approach. As pointed out by Söderbom et al. (2005), when the return to education is non-linear, control function estimators of the returns to schooling are likely to result in more precise estimates of schooling than 2SLS estimators. In addition, control function estimates of the returns to schooling are more robust than 2SLS estimators when slope parameters vary with unobserved factors (see also Card, 2001). Of course, a drawback of the control function approach is that it forces us to make (implicit) distributional assumptions which can be difficult to test.

A related modeling problem is that the benefits from participation might well be heterogeneous; those who lack alternative opportunities and have low earnings potential are likely to benefit more from program participation than individuals with high earnings potential. In particular, it is anticipated that the benefits from participating in the program are inversely related to the level of educational attainment. To allow for this possibility, the gains from participation are allowed to depend on observables following Blundell & Costa Dias (2002). Assuming a (log-linear Mincerian relationship between earnings, our estimable equation takes the form:

$$W = \alpha + \beta_X X + \beta_{T_j} D_j + \beta_{X T_j} X D_j + \theta(X, Z) + \varepsilon$$

where $\theta(X, Z)$ is a vector of terms that correct for endogeneity bias due to selection and the

⁸ This Lee selection correction (see Lee, 1983) is based on the multinomial logit model, which is appropriate since workers can be employed in 4 different types of firms; program contractors, non-program contractors, program constructors and non-program constructors. We also used the Dubin McFadden selection corrections (which outperform the Lee estimator if sample sizes are not too small as shown by Bourguignon et al. (2007)) but this led to very imprecise estimates. In addition, we explored the possibility of doing IV-estimation but could not find sufficiently convincing instruments. We also experimented with matching estimators, but do not present these as they do not allow for selection on unobservables and because results were very similar to those obtained by means of OLS.

endogeneity of schooling.⁹ These selection correction terms are a function of observables that affect both participation and earnings, X , and variables that affect participation only, Z , the exclusion-restrictions. Under the null hypothesis, program participation has no impact on earnings, i.e. $\beta_{TP}=0$ and $\beta_{XTP}=0$ where β_{TP} is the coefficient on the dummy that indicates that a worker is employed in a program (constructor) firm, while β_{XTP} is the coefficient on the interaction term between program participation and observable characteristics, X , intended to capture heterogeneity in the benefits of program participation. Such heterogeneity exist if the null hypothesis of homogenous returns, $\beta_{XTP}=0$ is rejected.

Table 8 presents the results from OLS estimation of earnings functions. Column 1 presents the results of regressing monthly income on days worked, a dummy for being a casual worker, gender, age and its square, years of schooling and its square, employment history dummies and firm type dummies, forcing the gains from program participation to be homogenous. The results are consistent with the literature; returns to schooling are convex,¹⁰ wages for casual workers are significantly lower than those for permanent workers, the age-earnings profile is concave, and the negative coefficient on the gender dummy attests to the existence of widespread discrimination against women in the labor market. Turning to the results of central interest, workers in program constructors earn 25% more than workers in non-program constructing firms, though there is a 60% premium associated with working for a contractor. In column 2 the assumption that the returns to schooling are homogeneous is relaxed and interactions between program participation and returns to schooling are included as additional regressors. While these interaction terms are not significant in this specification, their signs suggest that those with the least education benefit the most from partaking in the program.

In column 3 we allow for the endogeneity of education by including the predicted residual of a model of educational attainment and interactions of this residual with program participation as additional regressors. The model of educational attainment is presented in Table A2 in the appendix and uses distance to school at the age of six and parental occupation as exclusion restrictions. The terms are not jointly significant and parameter estimates do not change very much; the endogeneity of schooling is unlikely to be a serious problem as also evidenced by the Hausman test, which comfortably accepts the null hypothesis of no endogeneity of schooling.

We would like to know why program constructors pay more than non-program constructors and consider firm size, capital intensity and input intensity as candidate explanations.¹¹ Adding a control for firm-size in column 4 does not affect the pattern of results, which suggests that the program premium is not due to a positive association between firm size and wages.¹² To test whether capital- and input-intensity can explain the program premium, the capital-labor ratio and input-intensity are included as explanatory variables in columns 6 and 7. Unfortunately information on these variables is not available for all workers, forcing us to drop about 40% of our sample. For the resulting subsample the null hypothesis of heterogeneity in the treatment effect is rejected since the interaction terms between schooling and program participation are significant at the 10% level. In addition, the estimated program premium increases and is individually significant.¹³ Somewhat

⁹ Note that if returns to program participation are heterogeneous and program participation and schooling are both endogenous, we should also control for the endogeneity of the interaction of schooling and participation. In the context of our model this is done by interacting the terms correcting for selection bias with the terms which correct for the endogeneity of schooling.

¹⁰ Years of schooling and years of schooling squared are jointly significant at the 5% level.

¹¹ We also experimented with other firm characteristics, such as the age of the firm, the organizational structure of the firm (for example whether the firm is a cooperative or not), and the activities the firms engage in, but these variables could not explain why program firms pay more.

¹² Note that the sample has been reduced by 14 workers. However, differences in sample composition are not driving the results; estimates available upon request.

¹³ These are sample selection effects. To rule out the possibility that changes in coefficients are due to changes in the composition of the sample, specification 4 is re-estimated on the subsample of workers for whom information on the capital- and input- intensity of the firms they work in is available (see column 5). This subsample contains only 11 casual workers, which is reflected in the coefficients on days-worked and the casual dummy; both are now insignificant; the casual-dummy because it is imprecisely estimated; the days worked

surprisingly, capital per worker and inputs per worker are not significant predictors of earnings, while there seems to be a positive relationship between firm size and earnings.

Table 9 presents results using Lee's selectivity corrections (the underlying multinomial logit model for selection of workers into different types of firms is presented in the Appendix in Table A3 - prior activity and employment history dummies are used as exclusion restrictions), Columns 1 and 2 assume education is exogenous, while column 3 and 4 allow for the endogeneity of schooling. All specifications control for individual characteristics. Columns 2 and 4 also control for firm characteristics. None of the selection terms are individually or jointly significant in any of the specifications. In addition, resulting parameter estimates are very similar to OLS estimates. This indicates that endogeneity is not a major issue. Once again, the estimated return to program participation is higher for the subsample of observations for whom information on capital stock, input usage and size of the labor force is available (see columns 2 and 4). In addition, we can reject the null hypothesis of a homogeneous treatment effect for this subsample. Finally it should be noted that there is a positive association between firm size and wages.

In sum, the estimated program premium is rather robust and endogeneity is not of major empirical importance. The estimated premium is highest for the poorest workers. As a robustness check to test whether the IHDP indeed has had an equity enhancing impact on the earnings distribution quantile regressions were estimated. These regressions are presented in tables 10A and 10B and confirm that the program premium is highest for those at the bottom of the earnings distribution.

6. Summary and Conclusions

Active labor market programs, such as the AAIHDP, are widely viewed as a means to provide employment opportunities for the poor by providing more, relatively unskilled, jobs. To do that they must either use a more unskilled labor intensive technology or use more unskilled labor per unit of capital for a given technology. We have found that the technology of program firms is not significantly different from the technology used by firms outside the program, a conclusion which is robust to controlling for selection bias and endogeneity of factor inputs. Program firms are not more labor intensive and use more skilled labor than non-program firms.

We find there is an earnings premium associated with program participation which is heterogeneous and inversely related to educational attainment. It is unlikely to be driven by selection bias. It may reflect the fact that workers in program firms are often also the owners of such firms enables them to capture the return to capital. If this is the explanation then there is not a premium to labor for those participating in the program.

Given that the program has not altered technology or labor-intensity it is unlikely to have resulted in a higher level of labor demand than would have been generated had contracts been awarded to existing firms. Given the existence of excess demand and shortages of key construction inputs it is possible that the AAIHDP has led to some crowding out. The data at our disposal do not enable us to assess such general equilibrium effects quantitatively. These are an area for future research, as are the many dynamic issues that we could not explore.

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variable because variation in days worked among permanent workers is small. The implied age-earnings profile is anomalous but insignificant. The other coefficient estimates are rather stable.

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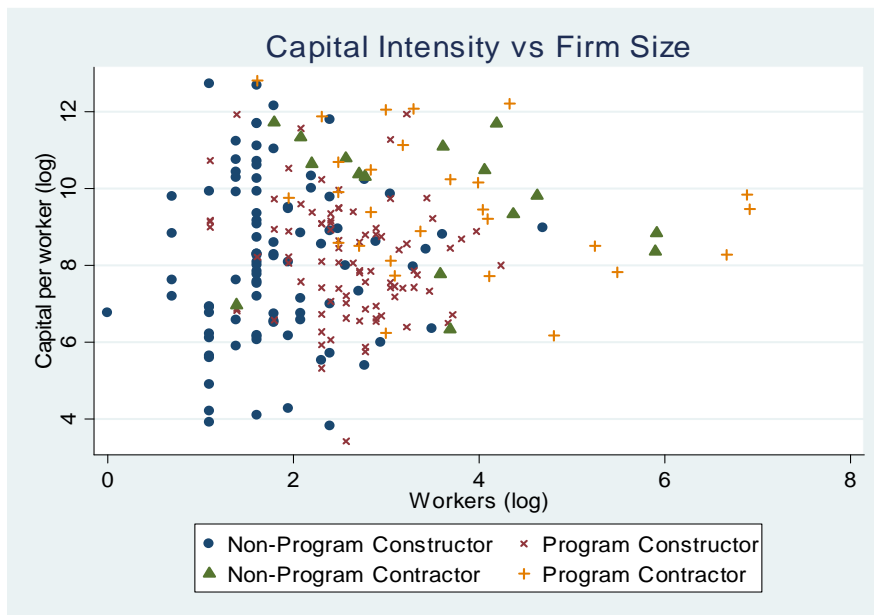
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TABLES AND GRAPHS

Graph 1: Capital Intensity vs Firm Size



Graph 2: Input Intensity vs Firm Size

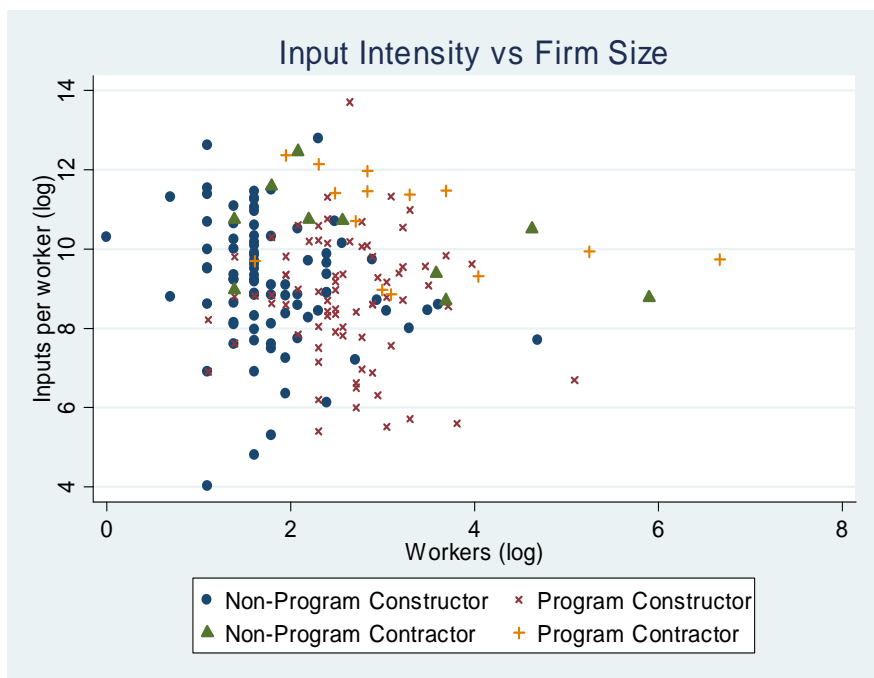


Table 1: Descriptive Statistics Firms

	Non-Program Constructor		Program Constructor		Non-Program Contractor		Program Contractor	
	mean	sd	mean	sd	mean	sd	mean	sd
Firm-age	3.78	4.33	2.27	1.80	6.95	4.90	6.65	6.00
Revenue								
Revenue (log)	11.56	1.39	11.94	1.26	13.92	1.59	14.30	1.59
Factors								
Workers (log)	1.86	0.68	2.56	0.62	3.09	1.48	3.33	1.37
Capital (log)	9.97	2.26	10.71	1.51	12.39	2.06	12.97	1.80
Inputs(log)	10.94	1.64	11.37	1.65	13.30	1.44	13.95	1.48
Capital per worker (log)	8.11	2.14	8.15	1.46	9.30	1.99	9.65	1.87
Labor intensity								
Inputs per worker(log)	9.09	1.62	8.81	1.50	10.20	1.33	10.62	1.25
Education of the workforce (years)	7.65	2.86	9.51	2.76	8.77	2.92	9.27	2.75
Characteristics of the workforce								
Age of the workforce	29.68	7.70	28.52	6.49	27.37	6.68	26.96	6.36
Labor force at startup (log)	1.49	0.87	2.40	0.84	1.92	1.60	2.83	1.25
Price Deflators								
Output price deflator	1.11	0.46	0.97	0.36	1.06	0.41	1.08	0.34
Input price deflator	1.01	0.45	1.03	0.40	0.93	0.41	0.91	0.33
Complete observations	78		70		9		13	

Note: All monetary measures in Ethiopian Birr (ETB). 1 USD dollar is worth approximately 9.1 Ethiopian Birr (ETB)

Table 2: Explaining Capital Intensity - OLS

Dependent variable: Log of Capital per worker

	(1)	(2)	(3)
Workers(log)	0.141 (0.12)	0.140 (0.12)	-0.213 (0.14)
Program-dummie		0.006 (0.27)	0.122 (0.26)
Contractor			1.766*** (0.35)
Constant	8.084*** (0.31)	8.083*** (0.31)	8.546*** (0.31)
N	222	222	222
R2	0.007	0.007	0.108
Adjusted R2	0.002	-0.002	0.096

Note: *, **, *** indicate significance at the 10%, 5% and 1% level respectively

Table 3: Explaining Input-Intensity - OLS

Dependent variable: Log of Input per worker

	(1)	(2)	(3)	(4)
Workers(log)	-0.135 (0.13)	-0.359** (0.14)	-0.346** (0.14)	-0.283* (0.15)
Program-Non-Contractor			-0.145 (0.26)	
Program-Contractor			0.536 (0.63)	
Contractor		1.901*** (0.36)	1.502*** (0.53)	1.586*** (0.38)
Capital-Labor-Ratio				0.201*** (0.06)
Program-dummie		-0.049 (0.25)		-0.097 (0.25)
Constant	9.459*** (0.32)	9.750*** (0.30)	9.767*** (0.30)	7.955*** (0.62)
N	185	185	185	175
R2	0.006	0.143	0.148	0.186
Adjusted R2	0.0005	0.129	0.129	0.166

Note: *, **, *** indicate significance at the 10%, 5% and 1% level respectively

Table 4: Production Functions - OLS

Dependent variable: Log of annual revenue

	All	Constructors	Constructors
	(1)	(2)	(3)
<i>Factors</i>			
Workers(log)	0.121 (0.12)	0.210 (0.17)	0.223 (0.17)
Capital(log)	0.046 (0.04)	0.046 (0.05)	0.041 (0.05)
Inputs(log)	.596*** (0.05)	.597*** (0.07)	.595*** (0.07)
<i>Activity Dummies</i>			
PCB	0.234 (0.21)	0.351 (0.25)	0.333 (0.25)
HCB	-0.068 (0.16)	0.054 (0.20)	0.085 (0.20)
Gravel	1.001** (0.46)	1.174** (0.52)	1.215 (0.52)
Wood	0.046 (0.17)	0.128 (0.20)	0.137 (0.20)
Wall	-0.079 (0.26)	0.040 (0.35)	0.052 (0.35)
Structural	0.468 (0.42)	0.375 (1.18)	0.367 (1.19)
Electrical	-0.357 (0.36)	-0.279 (0.45)	-0.291 (0.45)
Sanitary	.559* (0.32)	0.563 (0.37)	0.550 (0.37)
Finishing	0.097 (0.30)	0.060 (0.41)	-0.007 (0.41)
Other	0.270 (0.27)	0.271 (0.31)	0.320 (0.32)
Production-inputs	0.178 (0.24)	0.279 (0.28)	0.297 (0.29)
<i>Interaction Terms</i>			
Large-Contractor	-2.522** (1.26)		
Contractor*Workers	0.104 (0.18)		
Contractor*Capital	.222** (0.11)		
Program-dummie		0.883 (1.16)	0.682 (1.19)
Program*Workers		-0.233 (0.26)	-0.219 (0.26)
Program*Capital		-0.040 (0.10)	-0.029 (0.10)
Program*Inputs		-0.002 (0.10)	-0.002 (0.10)
<i>Human Capital</i>			
Education of the Workforce			0.028 (0.03)
Age of the Workforce			0.00002 (0.02)
Constant	4.245*** (0.54)	3.982*** (0.74)	3.789*** (0.90)
N	170	148	148
R2	0.775	0.669	0.672
Adjusted R2	0.75	0.623	0.62

Note: *, **, *** indicate significance at the 10%, 5% and 1% level respectively

Table 5: Production Functions – Instrumental Variable Estimation, Constructors only

Dependent variable: Log of annual revenue

	(1)	(2)	(3)	(4)	(5)
Factors					
Capital-per-worker (log)	0.035 (0.04)	0.049 (0.04)	0.090 (0.07)	0.035 (0.04)	0.042 (0.09)
Inputs-per-worker (log)	0.73*** (0.17)	0.596*** (0.05)	0.467*** (0.11)	0.708*** (0.18)	0.962*** (0.31)
The Impact of the program					
Program-Dummie		-0.489 (0.55)	-2.017 (1.88)	-0.396 (0.59)	5.215 (3.52)
Program-capital-per-worker (log)			-0.178 (0.26)		0.008 (0.34)
Program-Inputs-per-Worker (log)			0.305 (0.20)		-0.674 (0.49)
Activities					
PCB	0.032 (0.22)	0.323 (0.33)	0.451 (0.58)	0.229 (0.38)	0.551 (0.60)
HCB	-0.184 (0.24)	-0.037 (0.19)	-0.032 (0.20)	-0.147 (0.25)	-0.105 (0.29)
Gravel	0.978* (0.56)	0.827* (0.47)	1.29** (0.65)	1.04* (0.56)	0.364 (1.05)
Wood	0.068 (0.19)	0.094 (0.20)	0.059 (0.22)	0.116 (0.20)	0.172 (0.24)
Wall	0.018 (0.34)	0.043 (0.34)	0.275 (0.51)	0.087 (0.35)	0.013 (0.63)
Structural	-0.013 (1.17)	0.130 (1.13)	0.315 (1.25)	0.001 (1.16)	0.056 (1.37)
Electrical	-0.303 (0.43)	-0.272 (0.43)	-0.265 (0.47)	-0.283 (0.43)	-0.383 (0.51)
Sanitary	0.563 (0.39)	0.460 (0.35)	0.308 (0.40)	0.564 (0.39)	0.700 (0.50)
Finishing	0.041 (0.40)	-0.048 (0.39)	-0.138 (0.46)	-0.015 (0.40)	-0.041 (0.50)
Production-inputs	0.094 (0.36)	0.106 (0.35)	0.117 (0.54)	-0.030 (0.39)	-0.430 (0.62)
Other	0.291 (0.30)	0.260 (0.31)	0.090 (0.41)	0.224 (0.32)	0.327 (0.51)
Constant	2.695*** (1.32)	3.912*** (0.54)	4.859*** (0.94)	3.038** (1.46)	0.833** (2.60)
Endogenous					
Inputs per worker	Yes			Yes	Yes
Program Dummy		Yes	Yes	Yes	Yes
Program*inputs per worker			Yes		Yes
Program*capital per worker			Yes		Yes
Instruments Included					
Input Price	Yes			Yes	Yes
Labor force at startup		Yes	Yes	Yes	Yes
Lab force at start*inputspw			Yes		Yes
Lab force at start*capitalpw			Yes		Yes
Lab force at start*Input Price					Yes
Anderson LR	13.95	13.03	4.55	8.67	3.35
Cragg-Donald F	13.24	12.23	1.36	4.01	0.749
N	148	148	148	148	148
Hausman Chi(2) (df)	0.77(13)	0.39 (14)	4.50 (16)	0.96(14)	3.96(14)
Prob Chi(2)	1.00	1.00	0.99	1.00	0.99

Note: *, **, *** indicate significance at the 10%, 5% and 1% level respectively

Table 6: Descriptive Statistics Workers

	Non-Program Constructor		Program Constructor		Non-Program Contractor		Program Contractor	
	mean	Sd	mean	Sd	Mean	Sd	Mean	Sd
Age	28.62	8.63	28.65	6.85	30.51	7.61	27.62	6.41
Sex	0.81	0.40	0.85	0.36	0.86	0.35	0.77	0.42
Monthly pay(log)	5.77	0.76	6.12	0.84	6.52	1.00	6.42	1.01
Days worked per month(log)	3.05	0.40	3.09	0.34	3.01	0.49	3.13	0.27
casualdummy	0.23	0.42	0.22	0.42	0.27	0.45	0.29	0.46
(Highest level of) Educational Attainment								
Years of schooling	8.64	4.31	10.33	3.79	10.88	3.36	10.26	4.36
Primary	0.43	0.50	0.31	0.46	0.24	0.43	0.33	0.48
Secondary	0.47	0.50	0.65	0.48	0.67	0.47	0.59	0.50
College	0.01	0.08	0.01	0.09	0.02	0.14	0.03	0.17
TVETcomplete	0.15	0.35	0.35	0.48	0.27	0.45	0.39	0.49
Entire Employment History								
Apprenticeship completed in the past	0.25	0.44	0.46	0.50	0.35	0.48	0.39	0.49
Government employee	0.10	0.30	0.18	0.38	0.22	0.42	0.20	0.40
employee in a firm	0.42	0.49	0.44	0.50	0.51	0.51	0.44	0.50
Domestic employee	0.06	0.23	0.09	0.29	0.12	0.33	0.15	0.36
Family worker	0.03	0.17	0.03	0.17	0.00	0.00	0.05	0.21
Self-employed	0.07	0.26	0.06	0.24	0.08	0.28	0.05	0.21
Employed in a cooperative	0.02	0.14	0.14	0.34	0.04	0.20	0.08	0.27
Casual workers	0.12	0.33	0.09	0.29	0.08	0.28	0.03	0.17
Prior Activity								
Unemployed	0.20	0.40	0.17	0.38	0.14	0.35	0.21	0.41
Employee in a firm	0.25	0.43	0.31	0.46	0.41	0.50	0.36	0.48
Self employed	0.06	0.24	0.07	0.25	0.10	0.31	0.01	0.12
Casual workers	0.16	0.37	0.22	0.42	0.06	0.24	0.18	0.39
Student	0.22	0.41	0.16	0.37	0.24	0.43	0.15	0.36
Government Employee	0.04	0.21	0.04	0.19	0.02	0.14	0.07	0.26
Inactive	0.01	0.08	0.00	0.00	0.02	0.14	0.00	0.00
Instruments for educational attainment								
Distance to school (log)	3.34	0.75	3.19	0.71	3.20	0.65	3.12	0.66
Father was a farmer	0.37	0.48	0.24	0.43	0.20	0.41	0.32	0.47
Father was a civil servant	0.21	0.41	0.32	0.47	0.31	0.47	0.30	0.46
Mother was a farmer	0.15	0.36	0.11	0.31	0.10	0.31	0.06	0.24
Mother was a housewife	0.64	0.48	0.62	0.49	0.61	0.49	0.68	0.47
Complete observations	310		224		48		64	

Note: All monetary measures in Ethiopian Birr (ETB). 1 USD dollar is worth approximately 9.1 Ethiopian Birr (ETB)

Table 7: Being Hired by a Program Firm: Probit Selection Models

Dependent variable: working in a program firm

	(1)	(2)	(3)	(4)
Age	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	0.00
Primary	0.19	0.22	0.18	0.20
	(0.09)	(0.09)	(0.10)	(0.10)
Secondary	0.19*	0.23*	0.18	0.21*
	(0.09)	(0.09)	(0.10)	(0.10)
College	0.25	0.26	0.19	0.22
	(0.19)	(0.19)	(0.22)	(0.22)
TVET	0.19***	0.22**	0.19***	0.21***
	(0.05)	(0.05)	(0.06)	(0.06)
Sex	0.00	0.00	0.01	0.00
	(0.05)	(0.06)	(0.06)	(0.06)
Apprenticeship completed	0.17	0.15	0.16	0.15
	(0.04)	(0.04)	(0.05)	(0.05)
Activity Prior to Current Job				
-unemployed		0.15		0.14
		(0.12)		(0.12)
-employee		0.12		0.14
		(0.11)		(0.12)
-self-employed		0.03		0.13
		(0.14)		(0.17)
-casual		0.21		0.27
		(0.11)		(0.11)
-student		-0.03		0.07
		(0.12)		(0.12)
Employment History				
-unemployment			0.21***	0.20***
			(0.04)	(0.05)
-government			0.13	0.10
			(0.06)	(0.07)
-employee			-0.01	-0.05
			(0.04)	(0.06)
-domestic			0.20	0.17*
			(0.07)	(0.08)
-family worker			0.10	0.11
			(0.13)	(0.13)
-self-employed			-0.09	-0.08
			(0.09)	(0.12)
-cooperative			0.32***	0.31***
			(0.08)	(0.08)
-casual			-0.13	-0.17
			(0.07)	(0.07)
N	661	658	661	658
LR Chi2	101.6(17)	110.44(23)	153.69(25)	161.12(25)
Pseudo R2	0.1109	0.1282	0.1686	0.1774

Note:

-*, **, *** indicate significance at the 10%, 5% and 1% level respectively

-Marginal effects, evaluated at the mean

Table 8: Earnings Regressions - OLS

Dependent variable: log of monthly earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Days per month (log)	0.525*** (0.10)	0.519*** (0.10)	0.522*** (0.104)	0.542*** (0.11)	-0.208 (0.28)	-0.209 (0.28)	-0.230 (0.28)
CasualDummie	-0.377*** (0.09)	-0.385*** (0.09)	-0.384*** (0.073)	-0.425*** (0.10)	-0.412 (0.26)	-0.381 (0.26)	-0.413 (0.26)
Age	0.005 (0.02)	0.002 (0.02)	0.004 (0.026)	0.0009 (0.02)	-0.017 (0.03)	-0.021 (0.03)	-0.020 (0.03)
AgeSquared	0.007 (0.03)	0.010 (0.03)	0.006 (0.038)	0.011 (0.03)	0.035 (0.04)	0.039 (0.04)	0.039 (0.04)
Sex	0.383*** (0.08)	0.398*** (0.09)	0.399*** (0.084)	0.403*** (0.09)	0.359*** (0.11)	0.354*** (0.11)	0.373*** (0.11)
Schooling	-2.60e-06 (0.03)	-0.020 (0.04)	-0.021 (0.055)	-0.008 (0.04)	0.016 (0.05)	0.014 (0.05)	0.015 (0.05)
Schooling2	0.002 (0.00)	0.004* (0.00)	0.004 (0.003)	0.004 (0.00)	0.003 (0.00)	0.003 (0.00)	0.003 (0.00)
Program*Schooling		0.022 (0.07)	0.057 (0.114)	0.003 (0.07)	-0.079 (0.09)	-0.079 (0.09)	-0.078 (0.09)
Program*Schooling2		-0.003 (0.00)	-0.005 (0.005)	-0.002 (0.00)	0.0009 (0.01)	0.001 (0.01)	0.0008 (0.01)
Prior-Casualwork	0.214** (0.09)	0.213** (0.09)	0.213** (0.099)	0.243*** (0.09)	0.305*** (0.12)	0.298*** (0.12)	0.301*** (0.12)
Prior-employee firm	0.219*** (0.07)	0.216*** (0.07)	0.218*** (0.076)	0.221*** (0.07)	0.147 (0.09)	0.147 (0.10)	0.147 (0.09)
Appr. in the past	0.085 (0.07)	0.085 (0.07)	0.086 (0.065)	0.084 (0.07)	0.135 (0.09)	0.156* (0.09)	0.153 (0.09)
v			0.005 (0.025)				
v2			0.000 (0.004)				
v*program			0.003 (0.040)				
v2*program			0.003 (0.006)				
Contractor	0.711*** (0.13)	0.685*** (0.13)	0.685*** (0.136)	0.668*** (0.14)	0.716*** (0.21)	0.79*** (0.20)	0.653*** (0.22)
Program*Contractor	-0.204 (0.15)	-0.076 (0.34)	-0.250 (0.637)	-0.002 (0.35)	0.554 (0.48)	0.536 (0.48)	0.540 (0.48)
Program-Constructor	0.255*** (0.07)	0.348 (0.31)	0.188 (0.608)	0.417 (0.32)	0.849* (0.45)	0.915** (0.45)	0.861* (0.45)
Workers				0.024 (0.04)	0.085 (0.05)		0.103* (0.05)
Capital-Intensity						-0.008 (0.02)	-0.008 (0.02)
Input-Intensity						0.040 (0.03)	0.05* (0.03)
Constant	2.955*** (0.52)	3.028*** (0.53)	2.997*** (0.59)	2.857*** (0.54)	5.402*** (1.01)	5.334*** (1.03)	5.07*** (1.04)
N	550	550	550	536	345	345	345
R2	0.353	0.357	0.358	0.367	0.26	0.259	0.268
Adjusted R2	0.325	0.327	0.322	0.334	0.199	0.196	0.203

Note:

- Subcity dummies included but not reported
- Hausman test of endogeneity for column 3: Chi2(24)=0.72
- V is the residual from the education model
- Standard errors in column 3 bootstrapped.
- *, **, *** indicate significance at the 10%, 5% and 1% level respectively

Table 9: Earnings Regressions - Lee Selection Corrections

Dependent variable: Log of monthly earnings

	(1)	(2)	(3)	(4)
Days per month (log)	0.519*** (0.132)	-0.263 (0.28)	0.518*** (0.11)	-0.265 (0.28)
CasualDummie	-0.385*** (0.069)	-0.409 (0.26)	-0.386*** (0.09)	-0.405 (0.26)
Age	0.002 (0.022)	-0.019 (0.03)	0.005 (0.02)	-0.007 (0.03)
AgeSquared	0.010 (0.031)	0.037 (0.04)	0.005 (0.03)	0.021 (0.04)
Sex	0.398*** (0.069)	0.366*** (0.11)	0.401*** (0.09)	0.371*** (0.11)
Schooling	-0.020 (0.043)	0.015 (0.05)	-0.013 (0.05)	0.013 (0.07)
Schooling2	0.004 (0.003)	0.003 (0.00)	0.004 (0.00)	0.002 (0.00)
Prog*Schooling	0.022 (0.081)	-0.077 (0.09)	0.034 (0.07)	-0.057 (0.09)
Prog*Schooling2	-0.003 (0.004)	0.0009 (0.01)	-0.004 (0.00)	-0.0003 (0.01)
Prior-Casualwork	0.213** (0.102)	0.305*** (0.12)	0.21** (0.09)	0.299*** (0.12)
Prior-employee firm	0.216*** (0.068)	0.153 (0.09)	0.214*** (0.07)	0.146 (0.10)
ApprenticeshipCompleted	0.084 (0.065)	0.142 (0.09)	0.086 (0.07)	0.15* (0.09)
Contractor	0.347 (0.382)	0.452* (0.26)	0.676*** (0.17)	0.469* (0.26)
Program-Contractor	0.681*** (0.163)	0.499 (0.48)	-0.130 (0.36)	0.396 (0.49)
Program-Constructor	-0.077 (0.428)	0.781* (0.45)	0.316 (0.32)	0.719 (0.46)
Workers		0.115** (0.06)		0.11** (0.06)
Capital-Intensity		-0.002 (0.02)		-0.002 (0.02)
Input-Intensity		0.045 (0.03)		0.044 (0.03)
Lee	0.005 (0.144)	0.265 (0.20)	-0.032 (0.15)	0.216 (0.21)
V			-0.003 (0.04)	0.026 (0.05)
V2			-0.003 (0.01)	-0.003 (0.01)
VLee			0.009 (0.03)	-0.006 (0.04)
V2Lee			0.005 (0.01)	0.005 (0.01)
Constant	3.026*** (0.611)	4.994*** (1.04)	3.001*** (0.58)	4.937*** (1.06)
N	357	345	550	345
R2	550	0.272	0.359	0.275
Adjusted R2	0.325	0.205	0.322	0.198

Note:

- Subcity dummies included but not reported

- V is the residual from the education model

- Bootstrapped standard errors

- *, **, *** indicate significance at the 10%, 5% and 1% level respectively

Table 10A: Quantile Regressions - No Firm Controls

Dependent variable: Log of monthly earnings

	p10	p25	p50	p75
	(1)	(2)	(3)	(4)
Days per month (log)	0.641*** (0.14)	0.669*** (0.07)	0.562*** (0.08)	0.373*** (0.07)
Casual Dummie	-0.354*** (0.12)	-0.348*** (0.06)	-0.317*** (0.07)	-0.230*** (0.07)
Age	0.010 (0.02)	0.006 (0.01)	0.010 (0.01)	-0.043*** (0.01)
Age Squared	-0.002 (0.03)	0.001 (0.02)	-0.009 (0.02)	0.077*** (0.02)
Sex	0.39*** (0.11)	0.369*** (0.06)	0.359*** (0.06)	0.299*** (0.06)
Schooling	0.073** (0.03)	0.079*** (0.02)	-0.500** (0.02)	-0.021 (0.02)
Schooling2	-0.002 (0.00)	-0.002* (0.00)	0.005*** (0.00)	0.004*** (0.00)
Prior-Casualwork	0.150 (0.12)	0.071 (0.06)	0.011 (0.07)	0.160 (0.06)
Prior-employee firm	0.155 (0.11)	0.084* (0.05)	0.135** (0.05)	0.296*** (0.05)
Apprenticeship Completed	0.049 (0.10)	0.108** (0.05)	0.045 (0.05)	0.041 (0.05)
Contractor	0.681*** (0.18)	0.654*** (0.09)	0.647*** (0.09)	0.645*** (0.09)
Program-Contractor	-0.172 (0.22)	-0.148 (0.10)	-0.289 (0.11)	-0.188 (0.11)
Program-Constructor	0.265*** (0.10)	0.21*** (0.05)	0.147*** (0.05)	0.193*** (0.05)
Constant	1.42** (0.69)	2.017*** (0.36)	3.411*** (0.37)	4.842*** (0.34)
Pseudo R2	0.32	0.21	0.17	0.23
N	550	550	550	550

Note:

- *, **, *** indicate significance at the 10%, 5% and 1% level respectively

- Subcity dummies included but not reported

Table 10B: Quantile Regressions with Firm Controls

Dependent variable: Log of monthly revenue

	p10	p25	p50	p75
	(1)	(2)	(3)	(4)
Days per month (log)	0.107 (0.16)	-0.078 (0.29)	-0.107 (0.23)	-0.023 (0.17)
CasualDummie	-0.031 (0.09)	-0.214 (0.32)	-0.236 (0.26)	-0.124 (0.19)
Age	0.019 (0.02)	0.015 (0.03)	0.007 (0.03)	-0.045** (0.02)
AgeSquared	-0.006 (0.02)	-0.011 (0.04)	-0.001 (0.03)	0.077*** (0.03)
Sex	0.325*** (0.08)	0.334** (0.14)	0.346*** (0.11)	0.278*** (0.10)
Schooling	0.124*** (0.02)	0.038 (0.05)	-0.019 (0.04)	-0.014 (0.03)
Schooling2	-0.004*** (0.00)	0.0001 (0.00)	0.003 (0.00)	0.003 (0.00)
Prior-Casualwork	0.038 (0.08)	0.057 (0.16)	0.112 (0.12)	0.201* (0.11)
Prior-employee firm	0.081 (0.07)	0.077 (0.12)	0.012 (0.10)	0.233** (0.09)
Apprenticeship Completed	0.001 (0.07)	0.022 (0.12)	0.063 (0.09)	0.165** (0.08)
Contractor	0.686*** (0.10)	0.310 (0.24)	0.302 (0.22)	0.554*** (0.21)
Program*Contractor	-0.231* (0.14)	-0.201 (0.28)	-0.186 (0.24)	-0.113 (0.23)
Program-Constructor	0.172** (0.08)	-0.030 (0.13)	-0.029 (0.11)	0.009 (0.10)
Workers	0.067* (0.04)	0.166*** (0.06)	0.141** (0.06)	0.097* (0.06)
Capital-Intensity	0.029** (0.01)	0.036 (0.03)	0.019 (0.02)	0.006 (0.02)
Input-Intensity	0.027 (0.02)	0.077** (0.04)	0.035 (0.03)	0.038 (0.03)
Constant	2.087*** (0.69)	3.455*** (1.12)	4.838*** (0.87)	5.579*** (0.68)
Pseudo R2	0.22	0.14	0.15	0.21
N	345	345	345	345

Note:

- *, **, *** indicate significance at the 10%, 5% and 1% level respectively

- Subcity dummies included but not reported

APPENDIX: ADDITIONAL TABLES

Table A1.1: First Stage- IV - Columns 1 to 3

Column in IV	1	2	3	3	3
Dependent Variable:	Inputs per worker	Program Dummy	Program dummy	prog* inputs per worker	Prog*capital per worker
	(1)	(2)	(3)	(4)	(5)
Factors					
Capital-per-worker	0.152**	-0.015	0.033	0.204	0.116
	(0.06)	(0.02)	(0.04)	(0.36)	(0.33)
Inputs-per-worker		0.026	0.072	0.545	0.414
		(0.03)	(0.06)	(0.49)	(0.46)
Activities					
PCB	0.472	0.314***	0.354***	3.267***	3.298***
	(0.33)	(0.12)	(0.12)	(1.06)	(0.99)
HCB	0.89***	-0.035	-0.026	-0.276	-0.219
	(0.29)	(0.10)	(0.10)	(0.88)	(0.83)
Gravel	-2.120***	0.129	0.127	1.147	1.540
	(0.68)	(0.23)	(0.26)	(2.28)	(2.15)
Wood	-0.306	0.198**	0.182*	1.666*	1.149
	(0.30)	(0.10)	(0.10)	(0.86)	(0.81)
Wall	-0.540	0.091	0.086	0.914	1.622
	(0.51)	(0.17)	(0.17)	(1.52)	(1.43)
Structural	0.875	0.028	0.053	0.354	1.199
	(1.83)	(0.59)	(0.59)	(5.23)	(4.92)
Electrical	0.152	0.049	0.028	0.216	0.018
	(0.69)	(0.22)	(0.22)	(1.98)	(1.86)
Sanitary	-0.908	0.024	0.049	0.492	-0.176
	(0.56)	(0.18)	(0.18)	(1.63)	(1.54)
Finishing	-0.101	-0.133	-0.134	-1.163	-1.312
	(0.63)	(0.20)	(0.20)	(1.79)	(1.69)
Production-inputs	0.522	-0.307**	-0.334**	-3.237***	-3.081***
	(0.47)	(0.14)	(0.14)	(1.24)	(1.16)
Other	1.472***	-0.159	-0.150	-1.370	-1.606
	(0.39)	(0.15)	(0.15)	(1.35)	(1.27)
Instruments					
Labor-at-start	0.121***	0.164***	0.581*	2.186	1.682
	(0.03)	(0.05)	(0.28)	(2.52)	(2.37)
Labor-at-start*capital			-0.023	0.094	-0.104
			(0.03)	(0.24)	(0.22)
Labor-at-start*inputs			-0.028	-0.215	0.028
			(0.02)	(0.20)	(0.19)
Constant	7.063***	-0.005	-0.760	-5.168	-2.951
	(0.55)	(0.28)	(0.59)	(5.24)	(4.93)
N	148	148	148	148	148
R2	0.381	0.387	0.398	0.414	0.395
Adjusted R2	0.321	0.322	0.325	0.342	0.321

Note: *, **, *** indicate significance at the 10%, 5% and 1% level respectively

Table A1.2: First Stage- IV - Columns 4 and 5

Column in IV	4	4	5	5	5	5
Dependent variable:	Inputs per worker	Program Dummie	Inputspw	Program dummy	prog*inputspw	prog*capitalw
	(1)	(2)	(3)	(4)	(5)	(6)
Factors						
Capital-per-worker	0.153** (0.06)	-0.011 (0.02)	0.033 (0.13)	0.022 (0.04)	0.147 (0.37)	0.018 (0.33)
Activities						
PCB	0.529 (0.36)	0.329*** (0.12)	0.463 (0.37)	0.278** (0.11)	3.637*** (1.07)	2.775*** (0.93)
HCB	0.912*** (0.30)	-0.009 (0.10)	0.848*** (0.30)	-0.045 (0.09)	0.245 (0.87)	-0.399 (0.72)
Gravel	-2.044** (0.71)	0.080 (0.23)	-2.162*** (0.72)	0.281* (0.17)	-0.676 (2.10)	2.649* (1.40)
Wood	-0.326 (0.30)	0.189** (0.10)	-0.264 (0.30)	0.149* (0.09)	1.547* (0.88)	0.995 (0.72)
Wall	-0.490 (0.53)	0.079 (0.17)	-0.485 (0.52)	0.158 (0.14)	0.573 (1.53)	2.039 (1.18)
Structural	0.847 (1.84)	0.060 (0.59)	0.767 (1.83)	-0.354 (0.35)	0.894 (5.33)	-2.272 (2.90)
Electrical	0.149 (0.70)	0.049 (0.22)	0.169 (0.69)	0.220 (0.17)	0.274 (2.01)	1.253 (1.46)
Sanitary	-0.887 (0.57)	4.42e-06 (0.18)	-0.879 (0.56)	0.020 (0.16)	-0.035 (1.64)	-0.142 (1.31)
Finishing	-0.101 (0.63)	-0.138 (0.20)	-0.114 (0.63)	-0.097 (0.16)	-1.309 (1.83)	-1.088 (1.31)
Production-inputs	1.423*** (0.41)	-0.270** (0.13)	1.423*** (0.41)	-0.282** (0.12)	-2.298* (1.19)	-2.719*** (1.00)
Other	0.503 (0.47)	-0.149 (0.15)	0.514 (0.47)	-0.115 (0.12)	-0.949 (1.36)	-1.171 (0.99)
Instruments						
Inputprice	0.119*** (0.03)	-0.002 (0.01)	0.049 (0.05)	-0.010 (0.02)	-0.175 (0.15)	-0.103 (0.14)
Labor-at-start	-0.063 (0.15)	0.159*** (0.05)	-0.654 (0.56)	0.301* (0.17)	2.055 (1.62)	-0.004 (1.38)
Labatstart*inpprice			0.065* (0.04)	0.011 (0.01)	0.219* (0.12)	0.108 (0.10)
Labatsrat*cappw			0.067 (0.07)	-0.018 (0.02)	-0.135 (0.20)	0.125 (0.17)
Constant	7.175*** (0.61)	0.199 (0.20)	8.19*** (1.05)	-0.040 (0.33)	0.184 (3.05)	1.448 (2.73)
N	148	148	148	169	148	169
R2	0.382	0.382	0.398	0.386	0.39	0.392
Adjusted R2	0.317	0.317	0.325	0.321	0.315	0.328

Note: *, **, *** indicate significance at the 10%, 5% and 1% level respectively

Table A2: OLS -comparison IV production functions			
Dependent variable: Log of annual revenue			
Columns compared:	1	2 and 4	3 and 5
	(1)	(2)	(3)
<i>Factors</i>			
Capital-per-worker	0.055 (0.04)	0.053 (0.04)	0.047 (0.04)
Inputs-per-worker	0.586*** (0.05)	0.589*** (0.05)	0.605*** (0.07)
<i>The Impact of the program</i>			
Program-Dummie		-0.159 (0.17)	-0.027 (0.92)
Program-capital-per-worker			0.022 (0.09)
Program-Inputs-per-Worker			-0.036 (0.09)
<i>Activities</i>			
PCB	0.096 (0.22)	0.170 (0.23)	0.170 (0.22)
HCB	-0.050 (0.19)	-0.046 (0.20)	-0.045 (0.18)
Gravel	0.674 (0.45)	0.724 (0.46)	0.679 (0.45)
Wood	0.023 (0.19)	0.046 (0.19)	0.056 (0.19)
Wall	-0.063 (0.33)	-0.029 (0.33)	-0.050 (0.32)
Structural	0.154 (1.18)	0.146 (1.18)	0.121 (1.12)
Electrical	-0.294 (0.44)	-0.287 (0.44)	-0.286 (0.42)
Sanitary	0.424 (0.36)	0.436 (0.37)	0.457 (0.35)
Finishing	0.015 (0.40)	-0.005 (0.40)	0.001 (0.38)
Production-inputs	0.315 (0.26)	0.247 (0.27)	0.232 (0.27)
Other	0.360 (0.30)	0.328 (0.30)	0.341 (0.29)
Constant	3.754*** (0.52)	3.805*** (0.53)	3.709*** (0.62)
N	148	148	148
R2	0.6	0.603	0.603
Adjusted R2	0.561	0.561	0.555

Note: *, **, *** indicate significance at the 10%, 5% and 1% level respectively

Table A3: The determinants of educational attainment-OLSDependent variable: years of schooling

Age	0.571*** (0.09)
AgeSquared	-0.745*** (0.12)
Sex	0.173 (0.35)
Distance to school when 6	-0.640*** (0.20)
Father farmer	-2.513*** (0.38)
Father civil servant	1.193*** (0.32)
Mother farmer	-1.250*** (0.56)
Mother housewife	-0.605* (0.34)
Constant	3.134* (1.61)
N	592
R2	0.308
Adjusted R2	0.298

Note: *, **, *** indicate significance at the 10%, 5% and 1% level respectively

Table A4: Multinomial Logit Selection Model

	Program Constructor		Program Contractor		Non-Program Contractor	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Age	-0.01	0.02	0.04	0.03	-0.02	0.02
Primary Complete	0.78	0.49	-0.12	0.81	0.43	0.74
Secondary Complete	1.10**	0.50	0.66	0.80	0.29	0.74
College	0.57	1.33	0.80	1.55	1.24	1.30
TVET complete	0.70**	0.28	-0.21	0.48	1.34***	0.41
Sex	0.23	0.27	0.01	0.51	-0.25	0.38
Apprentice in the past	0.72	0.21	0.62	0.39	0.46	0.32
<i>Employment History</i>						
-ever unemployed	0.91	0.23	-0.35	0.39	0.55	0.34
-government employee	0.58	0.36	1.04**	0.56	0.79	0.52
-employee	-0.23	0.28	0.63	0.49	0.07	0.41
-domestic	0.67	0.41	0.91	0.62	1.55**	0.55
-self employed	-0.84	0.57	-1.82	0.98	0.18	0.86
-working in a coop	1.67	0.49	0.25	0.92	0.92	0.68
-casual worker	-0.66*	0.35	-0.35	0.65	-1.71**	0.79
<i>Activity Prior to Current Job</i>						
-unemployed	0.48	0.52	0.90	1.18	2.03	1.21
-employee	0.54	0.54	0.39	1.18	2.05	1.21
-self employed	1.24	0.76	1.63*	1.45	0.46	1.70
-casual worker	1.00*	0.54	-0.53	1.29	2.20	1.22
-student	0.34	0.53	1.03	1.17	1.46	1.25
-govt employee	0.32	0.74	-1.46**	1.61	1.92	1.38
N	661					
LR Chi2 (90)	912.41					
Pseudo R2	0.2067					

Note: *, **, *** indicate significance at the 10%, 5% and 1% level respectively