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Would more skills raise demand for those who do not get them? Evidence from South African Manufacturing

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Abstract

Policy makers claim a shortage of skills is constraining output and that a rise in skill supply would benefit less skilled occupations in South Africa. This assumes/implies skilled and unskilled labor are complements. To test the claim, this paper estimates Hicks Elasticities of Complementarity and elasticities of factor price with manufacturing data. Aggregate estimates suggest white collar labor complements blue collar labor, so a rise in skill supply would lead to a rise in demand for less skilled labor. Disaggregated results show skilled/artisanal and unskilled labor are complements while semi-skilled and unskilled labor are substitutes.

1 Introduction

"Government's ambition to grow [the] manufacturing base risks being stillborn unless the country addresses a worsening skills crisis." - Paton (2003:18)

The quote from a lead article in South Africa's *Financial Mail* articulates the widely held belief that artisans and other occupations are complements in production: there are limited opportunities for substitution by other inputs and the main effect of shortages is to lower output and thereby demand for all inputs. The official unemployment rate is about 25% (Statistics South Africa, 2007); much of it appears to be structural in that an oversupply of unskilled labor exists alongside 500 000 vacancies for skilled workers (Woolard, Kneebone & Lee, 2003). Vacancies are evidence of skills shortages constraining output, which implies filling them would allow production to expand and employment to rise for all occupations.

These observations imply skilled and unskilled labor are complements in production. The Hicks (1970) elasticity of complementarity (HEC) measures the percentage change in the ratio of endogenous factor prices to an exogenous change in their relative quantities. Similarly, the cross-elasticity of factor price measures the percentage change in a factor price in response to an exogenous change in another factor's quantity. If the effect is positive, the factors are said to be q-complements: if skilled and unskilled labor are q-complements, a rise in the supply of skilled labor would lead to a rise in unskilled labor demand. If the effect is negative, the factors are q-substitutes.

This paper estimates a translog production function to calculate Hicks elasticities of complementarity and cross elasticities between capital and five labor occupations. We also produce estimates using more aggregated groups, dividing the labor force into white collar and blue collar workers. The default statistics assume all factor prices are fully flexible and hence measure the impact on unskilled wages. However, it is important to allow for rigid wages in the South African context, so there are additional calculations such that changes in demand for unskilled labor manifest themselves as quantity changes.

The study closest in spirit to ours is by Mak (2000), who finds that workers with different education levels are q-substitutes in Canada. Grant & Hamermesh (1981) examine the interactions between youths, white women and other workers in the United States while Field (1988) investigates the HEC between free and slave labor. Vere (2001) finds the parameters for skilled and unskilled labor change over time in Taiwan. Similar methods continue to be used to study the effects of immigration on wages.[1]

[1] The thought experiments conducted are similar to ours in that estimates of the substitability between workers are used to infer the wage effects on each group induced by an immigration-induced supply shock. These include Borjas (2003), Ottaviano & Peri (2008) and Borjas, Grogger & Hanson (2008).

Our work complements contributions from the literatures on the returns to education and on economic growth. Martins & Pereira (2004) find that the returns to education are higher for those further up the earnings spectrum, which implies education received across the population could increase wage inequality. Cross-country studies (Temple, 2001; Bils & Klenow, 2000; Pritchett, 2001) have found correlations between the stock or flow of human capital and GDP levels or growth rates, but it is unclear whether the causal effects are large enough for those not receiving education to be better off. Given the resource costs of human capital investment, they may be worse off. Our work considers the possibility that inequality would rise because demand for unskilled labor would fall.

The South African case is an interesting one to study because attempts are being made to increase the supply of skills provision through schools, at the tertiary level, or through enterprise-based training. Van der Berg (2001) shows that the 1994 change of government induced major shifts of fiscal resources from traditionally white to traditionally black primary and secondary schools. In order to encourage firms to train their workers, the South African Skills Development Act of 1998 introduced a system where firms incur a tax on payroll, which is reduced if they equip workers with skills in cooperation with Sector Education Training Authorities (SETAs).

Production function estimation introduces the possibility of endogeneity bias. For panel data, Levinsohn & Petrin (2003) have suggested an intermediates proxy approach to address this potential problem. Our data is a single cross section of firms, as is the case for many developing countries.[2] We therefore adjust the intermediate proxy approach in order to estimate a translog function with cross-sectional data. We also make use of control variables reflecting the firms' information.

The key finding is that a rise in the supply of skilled/artisanal workers will increase unskilled labor demand while a rise in the supply of semi-skilled workers will reduce unskilled labor demand. Skilled/artisanal and unskilled labor are q-complements while semi-skilled and unskilled labor are q-substitutes. The findings are consistent with the view that a shortage of artisans is holding back production and that relieving the shortage will raise demand for unskilled labor. When we aggregate the occupations into blue and white collar workers, we find they are q-complemets, so a rise in the supply of white collar labor will raise demand for blue collar labor.

Section 2 compares the Hicks concept of substitutability between two inputs with the more common concept due to Robinson (1933). The Hicks concept is at the core of a multiple input model for the economy presented in section 3, which also shows how we can adjust the model

[2]Many new datsets administered by the World Bank, such as the Investment Climate Assessments or the Enterprise Surveys, are still single or repeated cross sections, but some are genuine panels.

to allow for rigid unskilled wages. Section 4 presents how the elasticities are calculated using translog production function estimates. Section 5 investigates empirical issues, including a description of the firm-level dataset. It also discusses how we address potential endogeneity bias. Section 6 presents the disaggregated results and section 7 presents aggregated findings. Section 8 concludes.

2 Two elasticity concepts: Hicks vs Robinson

> *"What now emerges is that [Joan Robinson] ought to have the sole right to the Elasticity of Substitution. Mine should have been defined by its reciprocal, which should have been given another name – Elasticity of Complementarity? It should then have been proved that in the two-factor case (alone) one was the reciprocal of the other."* – Sir John Hicks (1970:296)

This section introduces two distinct definitions of substitutability between factors, which happen to be equal in the two-factor context. We begin with a statement on the demand for a factor before making two alternative sets of assumptions, which allow us to describe the well-known-elasticity of factor demand on the one hand and the elasticity of factor price on the other. We will present a definition of substitutability applicable to each of these sets of assumptions and argue that the appropriate elasticity concept to incorporate into our model is the Hicks Elasticity of Complementarity.

We refer to the rules developed by Marshall (1920:383) using a linearly homogeneous production function with two factors for a firm in a perfectly competitive industry: $y = f(x_1, x_2)$. The price of output P is a function of industry output Y, $\frac{dP}{dY} \leq 0$. Wage equals marginal revenue product: $w_1 = Pf_1$ and $w_2 = Pf_2$. Hicks (1963:244) writes the own-elasticity of demand for x_1, $\frac{\partial \log x_1}{\partial \log w_1}$, as:

$$|\lambda_{11}| = \frac{\sigma\left(|\eta| + e_2\right) + s_1 e_2\left(|\eta| - \sigma\right)}{|\eta| + e_2 - s_1\left(|\eta| - \sigma\right)} \tag{1}$$

The demand for a factor in the industry is more elastic (high $|\lambda|$) if:

1. It can be easily substituted by the other factor (high σ)
2. Its share of revenue is higher (high s), provided $|\eta| > \sigma$
3. The supply of the other factor is more elastic (high e)
4. Product demand is more elastic (high $|\eta| \equiv -\frac{d\log Y}{d\log P}$)

Point 1 requires a measure of σ, which is a feature of the production technology. One definition is given in Robinson (1933):

$$\sigma_{12}^{R} \equiv -\frac{\partial \log \frac{x_1}{x_2}}{\partial \log \frac{f_1}{f_2}}, \tag{2}$$

where she assumes output and the price of the other factor are constant. σ_{12}^{R} is high if the factor is easily substituted by the other factor. When the supply of the other factor is perfectly elastic, $e \rightarrow \infty$ and we write (1) as:

$$|\lambda_{11}| \equiv \left|\frac{\partial \log x_1}{\partial \log w_1}\right| = \sigma_{12}^{R}(1-s_1) + s_1|\eta| \tag{3}$$

Here, σ_{12}^{R} captures the change in relative demand for the two factors due to the change in relative factor prices at constant output. For a fall in the price of one factor, profit maximizing industry output will rise and so will demand for both factors. However, as industry output rises, the product price falls, which mitigates the increase in demand for both factors. The second term captures the output effect. A measure of the compensated elasticity of labor demand, which does not allow for output effects, is given by:

$$|\bar{\lambda}_{11}| \equiv \left|\frac{\partial \log x_1}{\partial \log w_1}\right|_{Y} = \sigma_{12}^{R}(1-s_1) \tag{4}$$

An alternative to Robinson's measure of σ is given by Hicks (1932,1963), who introduces

$$\frac{1}{H_{12}} \equiv \frac{f_1 f_2}{f f_{12}}, \tag{5}$$

where f_{12} gives the rate of change of the marginal product of one factor for a change in the quantity of the other factor. As presented in Hicks (1963:245), $\sigma = \frac{1}{H_{12}}$ is increasing in the "facility of substitution" of the factors. Hicks' measure assumes the quantity of the other factor and the output price are constant. With $e = 0$ we get a measure of the inverse demand for the factor from (1):

$$|\hat{\epsilon}_{11}| \equiv \left|\frac{1}{\lambda_{11}}\right| \equiv \left|\frac{\partial \log w_1}{\partial \log x_1}\right| = H_{12}(1-s_1) + \frac{s_1}{|\eta|} \tag{6}$$

$\hat{\epsilon}$ is the elasticity of factor price (Hamermesh, 1993). It describes the change in factor price necessary for firms to absorb the extra supply of that factor in production. Here, H_{12} captures the percentage change in relative factor prices that must take place after a change in relative factor quantities, assuming output price is constant. After a rise in factor supply, output expands. However, expanded output lowers price, which lowers the marginal revenue product of the factors and therefore means the price of factor x_1 must fall by more. The second term therefore acts to make $|\hat{\epsilon}_{11}|$ higher. If we assume perfectly elastic product demand, then:

$$|\epsilon_{11}| \equiv \left| \frac{\partial \log w_1}{\partial \log x_1} \right|_P = H_{12}(1 - s_1) \tag{7}$$

Inspection of (7) and (4) show what appears to be a duality between H_{12} and σ^R_{12}. Hicks (1963:373) shows that, in the two factor case we have considered so far, $\sigma^R_{12} = \frac{1}{H_{12}}$. Unless one is willing to impose a number of restrictions on the production technology, the simple relationship ends when there are more than two factors.[3]

Hicks (1970) labelled H the "elasticity of complementarity" (HEC). Factors 1 and 2 are q-complements if $H_{12} > 0$. They are q-substitutes if $H_{12} < 0$. If two factors are q-complements, then a rise in supply of the one factor will lead to a rise in the wage of the other factor. If they are q-substitutes, a rise in the supply of one factor will lead to a fall in the wage of the other factor. In the two factor setting considered so far, the factors are necessarily complements, but this does not hold for the multiple factor case modelled in the next section.

3 A multi-factor model of exogenous input quantity changes

This section presents a multiple factor model for the economy, which we assume consists of a single homogeneous industry. It models the effect of an exogenous increase in the quantity of a factor on demand for other factors, as measured by the effect on wages. This assumes quantities are exogenous and wages are endogenous, not the other way around, and the HEC is therefore the more appropriate concept to measure.[4] Assuming an exogenous increase in inelastic factor supply is appropriate because, like the Department of Labor (1997), we believe it is the supply of schooling/education/training rather than demand that has thus far constrained skill acquisition in South Africa. The assumption that wages are fully flexible is more difficult to justify, because collective bargaining and other labor market institutions have driven up the costs of labor above clearing levels, particularly at the bottom of the skill spectrum (Fallon & Lucas, 1998). Therefore, we augment the standard model with one

[3] Allen (1938) extends Robinson's concept to multiple factors. See Sato & Koizumi (1973) and Syrquin & Hollander (1982) for more detailed relationships between the two elasticity concepts.

[4] With a number of technological restrictions on the substitutability between factors, one can legitimately use $\frac{1}{\sigma^R}$ to infer wage effects. For a discussion of interpretation when imposing a multi-level constant elasticity of substitution structure, see Ottaviano & Peri (2008).

which allows for less skilled wages to be rigid.

3.1 Fully flexible wages

Our economy uses n exogenously supplied factor inputs, with factor prices adjusting to ensure full employment in this section. Economy-wide output (Y) is determined by factor input quantities (X_i) according to a linearly homogeneous technology utilized by all h representative firms in the economy.

$$Y = f(X_1, ..., X_n) = hf(x_1, ..., x_n)\ , x_i = \frac{X_i}{h} \tag{8}$$

The price (P) received by firms is determined by aggregate output.

$$P = P(Y), \frac{dP}{dY} \leq 0 \tag{9}$$

Profit maximizing firms pay each input a wage (w_i) equal to its marginal revenue product, which is a function of the supply of all the inputs in the economy.

$$w_i = P(Y)f_i(X_1, ..., X_n), \quad f_i \equiv \frac{\partial f}{\partial X_i} > 0 \tag{10}$$

A change in factor supply has two effects on wages. First, it changes overall output and hence prices and, second, it changes the marginal rate of technical substitution given by the production technology, as shown respectively by the first and second terms of (11):

$$\frac{\partial w_i}{\partial X_j} = \frac{dP}{dY} f_i f_j + P f_{ij}, \text{where } f_{ij} \equiv \frac{\partial^2 f}{\partial X_i \partial X_j},\ f_{ii} < 0 \tag{11}$$

Converting to elasticity form:

$$\frac{\partial \log w_i}{\partial \log X_j} = \frac{X_j f_i f_j}{w_i} \frac{dP}{dY} + \frac{P f_{ij} X_j}{w_i} \tag{12}$$

$$= \frac{X_j f_i f_j P}{w_i f} \frac{1}{\eta} + \frac{f_{ij} f}{f_i f_j} \frac{f_i f_j P X_j}{f w_i}, \tag{13}$$

$\eta < 0$ is the elasticity of product demand in the economy. The Hicks elasticity of complementarity between factors i and j is:[5]

$$H_{ij} = \frac{f_{ij} f}{f_i f_j} \tag{14}$$

Factor j's share of output is given by:

$$s_j = \frac{f_j X_j}{f(X_1, ..., X_n)} \tag{15}$$

Together with equation (10), this can be used to rewrite (13) as:

$$\frac{\partial \log w_i}{\partial \log X_j} \equiv \hat{\epsilon}_{ij} = s_j \left(H_{ij} - \frac{1}{|\eta|} \right) \tag{16}$$

$\hat{\epsilon}_{ij}$ is the elasticity of factor price. A rise in the supply of a factor works through 3 channels. (i) Output is determined by the supply of factors, so a rise in the supply of a factor necessarily leads to a rise in output and demand for all other factors. ii) This effect is mitigated because a rise in output leads to a fall in product price and hence a fall in factor demand. iii) The nature of the technological relationship between factors means $f_{ij} \lesseqgtr 0$ for $n > 2$ and $i \neq j$. As $|\eta| \to \infty$, the effect of (ii) disappears. ϵ_{ij} is the elasticity of factor price when product prices are constant.

$$\epsilon_{ij} = s_j H_{ij} \tag{17}$$

After a change in the quantity of one factor, a new vector of factor prices will restore equilibrium in the n factor markets. Equations (16) or (17) can be interpreted as the change in each of the n factor prices necessary for the economy to generate factor demand equal to the new factor supply; that is, to accommodate the change in supply of one factor and keep demand for all other factors equal to their (unchanged) supply.

$\epsilon_{ij} \geq \hat{\epsilon}_{ij}$ so, unlike other documented work, this study allows for product price effects. To do this, we calculate values of η that would make $\hat{\epsilon}_{ij}$ equal to zero. Calling this threshold η^*, (16) shows $\eta^* = -H_{ij}^{-1}$ for strictly positive factor shares. If the elasticity of product demand is η^* or less elastic, then a positive elasticity of factor price ($\epsilon_{ij} > 0$) would become negative ($\hat{\epsilon}_{ij} < 0$). The more inelastic demand must be, the less likely it is that we are incorrectly predicting two factors are q-complements.

Another potential adjustment to ϵ_{ij} accommodates the possibility that the wage of one factor is rigid, as discussed next.

[5] This is the same value at economy and firm levels, because $f(X_1, .., X_n) = hf(x_1, ..., x_n)$, $f_i(X_1, ..., X_n) = f_i(x_1, ..., x_n)$ and $f_{ij}(X_1, ..., X_n) = h^{-1} f_{ij}(x_1, ..., x_n)$ for a linearly homogeneous technology.

3.2 A rigid wage

Given that wages may be rigid and that we do see unskilled unemployment in South Africa and other developing countries, we employ the methods first used by Johnson (1980). In the case where only one factor's wage is completely rigid, we can calculate the effect of an exogenous change in the quantity supplied of another factor on the employment of that factor. This means the HEC can be used to infer effects on employment rather than wages for a particular factor.

The approach followed here is to assume demand for unskilled labor is constrained by a rigid wage.[6] Following Grant & Hamermesh (1981), assume all factors' prices are flexible except for unskilled labor, which has wage w_u. All factor quantities are fixed except unskilled labor, which has quantity employed X_u. In this model, we do not allow for changes in product price and set $P = 1$ on the assumption of perfectly elastic product demand. The marginal productivity conditions are:

$$w_u = f_u(X_u, X_2, ..., X_n) \tag{18}$$

$$w_i = f_i(X_u, X_2, ..., X_n), \quad i = 2, ..., n \tag{19}$$

Differentiating the equations with respect to X_j and solving the resulting system:

$$\frac{\partial X_u}{\partial X_j} = \frac{-f_{uj}}{f_{uu}} \tag{20}$$

$$\frac{\partial w_i}{\partial X_j} = \frac{-f_{iu}f_{uj} + f_{ij}f_{uu}}{f_{uu}}, \quad i = 2, ..., n \tag{21}$$

Using equation (15), $X_i = \frac{fs_i}{f_i}$ and, by equation (14), $f_{ij} = \frac{f_i f_j H_{ij}}{f}$. Hence:

$$\frac{\partial \log X_u}{\partial \log X_j} \equiv \rho_{uj} = \frac{-H_{uj}s_j}{H_{uu}s_u} \tag{22}$$

$$\frac{\partial \log w_i}{\partial \log X_j} \equiv \epsilon_{ij}^{\rho} = \frac{s_j\left(-H_{iu}H_{uj} + H_{ij}H_{uu}\right)}{H_{uu}}, \quad i = 2, ..., n \tag{23}$$

As presented in Grant & Hamermesh (1981), equations (22) and (23) demand a burdensome calculation of coefficients and p-values. However, simply using (17) can aid in computation

[6] In contrast, the mechanism in Borjas, Grogger & Hanson (2006) is that a reduction in the wage discourages that group from participating in the formal labour market.

and interpretation:

$$\rho_{uj} = \frac{\epsilon_{uj}}{-\epsilon_{uu}} \tag{24}$$

$$\epsilon_{ij}^{\rho} = \epsilon_{ij} - \frac{\epsilon_{iu}\epsilon_{uj}}{\epsilon_{uu}} \tag{25}$$

ϵ_{uj}, ϵ_{ij}, ϵ_{uu} and ϵ_{iu} represent what the elasticities would have been if all wages were flexible. It is therefore possible to infer the effects of a change in the quantity of a factor on the employment of unskilled labor (equation (24)) or on the prices of other factors (equation (25)), taking unskilled wage rigidity into account. Consider the case where $\epsilon_{uj} > 0$ such that the demand for unskilled labor rises after a rise in the supply of X_j. If wages were flexible, this would manifest itself as a rise in unskilled wages. Intuitively, ϵ_{uu} reflects f_{uu} and the slope of the labor demand curve. A low value of $|\epsilon_{uu}|$ entails slowly diminishing marginal product and a flat labor demand curve, which means a given rightward shift in the labor demand curve would translate into a relatively large shift in the quantity of labor demanded at the given unskilled wage.

4 Elasticities and translog production functions

To find the elasticities of interest, we need the parameters of the underlying technology. The estimation of a production function with exogenous input quantities, rather than a cost function with exogenous input prices, is consistent with the assumptions underlying the HEC and elasticity of factor price. The possibility that input quantities are endogenously chosen by the firm is an estimation issue discussed in section 5. Furthermore, production function estimates provide a far more tractable method for calculating the HEC and elasticities of factor price.[7] This study uses translog functions, which were developed by Christensen, Jorgenson & Lau (1973) and recently employed to estimate H by Mak (2000).

$$\log q = \log \alpha_0 + \sum_i \alpha_i \log x_i + \frac{1}{2} \sum_i \sum_j \beta_{ij} \log x_i \log x_j \tag{26}$$

q is a measure of the value of output and x_i, x_j are inputs earning $w_i = \frac{\partial q}{\partial x_i}, w_j = \frac{\partial q}{\partial x_i}$.

Borjas (2003) develops a CES structure, which imposes a variety of restrictions. All education types would have the same degree of substitutability. By constructing a multiple-level structure, Ottaviano & Peri (2008) relax this restriction somewhat. However, the *sign* of the elasticity is still necessarily imposed such that one is making the inputs q-complements

[7]See Sato & Koizumi (1973) for the cost function approach to estimating H.

by construction. In contrast, the translog function does not impose such priors on the signs of the elasticities.

The number of parameters to be estimated is large, but can be reduced: Slutsky symmetry conditions $\beta_{ij} = \beta_{ji}$ are imposed in the construction of the variables. Furthermore, technological features can be tested for and imposed. Equation (26) is homogeneous of degree k if:

$$\sum_j \beta_{ij} = \sum_i \beta_{ij} = 0 \text{ and } \sum_i \alpha_i = k \tag{27}$$

If $k = 1$, there are constant returns to scale (Chung, 1994). Differentiating (26) with respect to $\log x_i$ yields

$$\frac{\partial \log q}{\partial \log x_i} = \alpha_i + \sum_j \beta_{ij} \log x_j, \tag{28}$$

but

$$\frac{\partial \log q}{\partial \log x_i} = \frac{\partial q}{\partial x_i}\frac{x_i}{q} = \frac{w_i x_i}{q} = s_i, \tag{29}$$

which is the share of factor i in the value of output. Therefore:

$$s_i = \alpha_i + \sum_j \beta_{ij} \log x_j \tag{30}$$

It is common to estimate the system of equations (30) to improve efficiency characteristics (Berndt, 1991; Mak, 2000). However, in the data used for this paper, factor shares are not available, so the parameters estimated in (26) are used to predict s_i and calculate elasticities. $w_i = \frac{q}{x_i} s_i$, so

$$\frac{\partial \log w_i}{\partial \log x_j} = \frac{x_j}{w_i}\frac{\partial}{\partial x_j}\left(\frac{q}{x_i} s_i\right) \tag{31}$$

Differentiating (26), holding the product price component of q constant and recalling $\frac{\partial q}{\partial x_j} = w_j$:

$$\frac{\partial \log w_i}{\partial \log x_j} = \frac{x_j}{w_i}\left(\frac{q\beta_{ij}}{x_i x_j} + \frac{w_j s_i}{x_i}\right) = \frac{\beta_{ij}}{s_i} + s_i\left(\frac{w_j x_j}{q}\right)\left(\frac{q}{w_i x_i}\right) \tag{32}$$

Therefore:

$$\epsilon_{ij} = \frac{\beta_{ij}}{s_i} + s_j \tag{33}$$

By (17):

$$H_{ij} = \frac{\beta_{ij}}{s_i s_j} + 1 \tag{34}$$

Furthermore (Binswanger, 1974):

$$\epsilon_{ii} = \frac{\beta_{ii}}{s_i} + s_i - 1 \tag{35}$$

$$H_{ii} = \frac{\beta_{ii}}{s_i^2} + 1 - \frac{1}{s_i} \tag{36}$$

5 Empirical issues

This section introduces the data used for estimation of α and β and argues why estimates based on firm-level data are informative for calculating elasticities for the economy. This hinges on how easily we can move between descriptions of firm-level activity and economic implications at a sector (manufacturing) level and needs manufacturing to be sufficiently representative of the whole economy. This is distinct from the issue of what can be taken as given at the firm-level as opposed to the broader economy: while the theoretical model of economy-wide effects can legitimately take the factor inputs as given, this is not true at the firm level. This motivates a discussion of endogeneity bias and our proposed remedies. Furthermore, we discuss issues of inference on the non-linear elasticity estimates as well as theoretical and empirical aspects of separability, which informs whether we can adopt the value added specification and/or aggregate our inputs.

5.1 Data from the firm-level manufacturing survey

The data set is the 1998 National Enterprise Manufacturing Survey. After adjusting for non-response and outliers and because we only choose to use firms that have a value added of more than one million Rand, the number of firms in the sample is abut 250. Descriptive statistics of the key production function variables are in Table A1, but for a thorough analysis of the data, see Bhorat & Lundall (2002). The variables for the production function are the capital stock[8] and employment numbers by occupation group.[9] The five occupations are:

- Managerial/Professional
- Sales/Clerical
- Skilled/Artisan (eg technicians, welders)
- Semi-skilled (eg machinery operators)

[8]Default regressions adjust the capital stock for shift capacity utilization, although results were robust to the use of unadjusted measures. Our implementation of a Levinsohn Petrin (2003) procedure uses the unadjusted measure of the capital stock.

[9]We account for part-time workers by giving them a weight of 0.5.

- Unskilled (eg laborers)

A high degree of disaggregation is a key feature of our data. In recent work, Borjas, Grogger & Hanson (2008) generate a high degree of disaggregation using household data to classify workers by education level and their degree of experience, but we do so by occupation. Disaggregated estimates use all five occupations while aggregated estimates combine the Managerial/Professional and Sales/Clerical occupations into white collar workers and aggregate the Skilled/Artisan, Semi-skilled and Unskilled occupations into blue collar workers. Semi-skilled workers make up about 40% of the total workforce, unskilled workers comprise about 30% and skilled/artisanal workers comprise about 10%. About 80% of the workforce is blue collar and 20% is white collar.

There is information on what percentage of total costs is comprised of raw materials costs, but there is no data on total costs or on raw materials costs. To derive a measure of raw materials costs, it is necessary to assume that turnover equals total costs. Then raw materials as a percentage (p) are multiplied by turnover (q) to get raw materials. Value added is constructed as sales minus raw materials so that:

$$v = (1 - p)q \tag{37}$$

5.2 Firm-level data for a macro model

In this section, there are three issues that must be considered when using cross-sectional firm-level manufacturing information about α and β to generate elasticities for the economy. The first is that the phenomenon we are contemplating is one that necessarily would occur over time. In an ideal world, we would use variation in time series data at the macroeconomic level to estimate the parameters. However, data with a suitable disaggregation of skill do not exist yet. Our objective is therefore to use cross sectional data to estimate the technological parameters and infer what the demand effects would be *if* skill supply rises.

The second is whether we can consider many representative firms and one single firm for the economy/industry interchangeably. The assumption of constant returns to scale in the model, which we verify empirically in section 6, allows us to do this. This means we can use variations across firms in their inputs to estimate the parameters of an aggregate production function. Microeconomic census data has been used to estimate an aggregate technology and make inferences about economy-wide wage effects by Borjas (2003) and Ottaviano & Peri (2008).

The third issue arises from our use of manufacturing data. Applying evidence from manufacturing to the whole economy would be problematic if the production technology is fundamentally different in manufacturing compared to other sectors. However, manufacturing is the largest sector in the South African economy. Furthermore, the data classification and structure of the economy means manufacturing includes a particularly wide range of economic activity by international standards, ranging from the beneficiation of primary commodities to relatively service intensive industries. This means manufacturing data is quite representative of the economy. (Bhorat & Hodge, 1999; Wood, 1995). Using the data to make inferences about manufacturing alone would require relaxing the assumption of perfectly exogenous labor supply at the cost of far greater complexity. Being fully aware of these issues, Grant & Hamermesh (1981) choose to employ cross-sectional manufacturing data while Borjas (1986) yields the same results from estimates for the whole economy and for manufacturing alone.

Although we assume homogeneity in the α and β parameters of the production technology, there may be some variation in the intercept term. For example, owner-managed or export-oriented firms may be more efficient users of their inputs. Therefore, we include a number of controls to reduce the standard errors of the estimates.

5.3 Separability

Separability permits the legitimate use of the value added specification and/or the aggregation of factors. Our main motivation for using the value added specification, where raw materials are omitted and value added (rather than turnover) is used as the measure of the value of output, is a reduction in the number of parameters to be estimated. It also tended to produce more reliable results.[10] Aggregation may be desirable for various reasons. It is less demanding of the data and many theoretical models employ a single elasticity between skilled and unskilled labor, often represented by white and blue collar workers. Thus, in addition to the disaggregated results with five labor inputs, we will present aggregated results with two labor inputs.

Sato (1975) shows weak separability with respect to raw materials justifies the value added specification. Drawing on Berndt & Christensen (1973ab), a translog production function is weakly separable with respect to input x_r if:

$$s_i\beta_{jr} - s_j\beta_{ir} = 0 \tag{38}$$

$s_i, s_j > 0$ so strong separability holds if:

$$\beta_{ir} = 0 \ \forall i : i \neq r \tag{39}$$

[10] Chung (1994) contains studies adopting the value added specification.

If (39) does not hold for some β_{ir}, we can draw on Berndt & Christensen (1973b) to establish the condition for weak separability:

$$\frac{\alpha_i}{\alpha_j} = \frac{\beta_{ii}}{\beta_{ij}} = \frac{\beta_{ij}}{\beta_{jj}} = \frac{\beta_{ir}}{\beta_{jr}} \tag{40}$$

This must hold for each factor pair x_i, x_j whose elasticity we wish to obtain. We tested restrictions of the form (39) or (40) using Wald tests on turnover regressions. Tests of (39) were rejected but tests of weak separability for each combination of factors with raw materials did not reject separability. Most p-values were well above 0.90.[11] The tests therefore justify the use of the value added specification in the production function. To aggregate factors x_i and x_j, they must be weakly separable from all others in the production function such that:

$$s_i\beta_{jk} - s_j\beta_{ik} = 0 \ \forall k : k \neq i, k \neq j \tag{41}$$

To combine occupations types j in set J into an aggregate - for example combining managers/professionals and sales/clerical workers into a white collar aggregate - a sufficient condition is that:

$$\beta_{jk} = 0 \ \forall j : j \in J, k \notin J \tag{42}$$

The discussion of results will confirm that this holds.

5.4 Endogeneity bias

We have discussed whether parameter estimates based on firm-level data can be used to calculate elasticities for the broader economy. This section addresses the issue of consistent estimation of those parameters. A default stochastic specification for value added would take the form:

$$\log v = \log \alpha_0 + \sum_i \alpha_i \log x_i + \frac{1}{2}\sum_i \sum_j \beta_{ij} \log x_i \log x_j + \omega \tag{43}$$

Valid estimation by ordinary least squares (OLS) requires the errors to be orthogonal to the inputs. As argued by Marschak & Andrews (1944), while exogeneity of the inputs is arguably valid for the economy as a whole, it is not justified at the firm level. We can decompose the error into two components so that $\omega = I + \mu$. μ represents mean zero errors made by firms in

[11] Results are available on request. When performing multiple tests, it is arguably appropriate to make an adjustment to the statistics used in each test to prevent the false rejection of the null hypothesis. We perform Wald tests which do and don't adjust the probability values required for each restriction. We use the Sidak adjustment(see Statacorp, 2003). The choice of method does not appear to matter. Even were we not to make such an adjustment, we still fail to reject weak separability.

the use of the inputs they have available. While μ is orthogonal to the inputs by assumption, each firm chooses its inputs using private information (I) not observed by the econometrician. For example, I may contain information on an improved market outlook, which would lead to increased use of inputs and higher value added. In equation (43) ω would be positively correlated with x_i, causing biased estimates. Although it is difficult to judge direction with many inputs (Greene, 2003), it is likely the bias would be upwards. Inputs that are more flexible would tend to be biased the most.

Griliches & Mairesse (1995) observe a number of responses to endogeneity, including approaches aimed at controlling for the private information on the one hand and instrumental variables methods on the other. Our application would require an extraordinarily large number of instruments, which effectively denies us the option of performing standard two stage least squares (2SLS). For a translog function, we would need one instrument to identify each of the six inputs and their interactions. However, using a simpler Cobb Douglas specification, results suggest that the use of OLS with proxies is superior to the use of 2SLS.[12]

One can try to control for the unobserved information in the error term through proxies, which are variables that are correlated with I because they give an indication of the firm's expectations of conditions for the relevant time period. Amongst our set of firm-specific controls, we have information on the firm's expected price change for the year and on the firm's expected impact of changes in labor legislation. Thus, one strategy controls for I using control variables c such that the remaining components of the error term are orthogonal to the inputs:

$$\log v = \log \alpha_0 + \sum_i \alpha_i \log x_i + \frac{1}{2}\sum_i \sum_j \beta_{ij} \log x_i \log x_j + c + \mu \tag{44}$$

Rather than proxy I with what firms *say*, we can proxy I with what they *do*. Levinsohn & Petrin (2003) establish conditions under which including variables for observed investment in intermediate goods to proxy for unobserved shocks generates consistent estimates of the other inputs. The effectiveness of the "intermediates proxy" (IP) approach is contested (Ackerberg et al, 2005), but we nonetheless adapt it to our data as a robustness check.

[12] We estimated a Cobb Douglas function with controls and compared the results to 2SLS. The Hausman specification test for endogeneity finds a p value of 0.90 for the null hypothesis that the coefficients do not differ systematically, so there is no endogeneity bias. A Hausman test does not reject the exogeneity of the instruments at the 20% level. Besides, standard errors on each of the factor inputs are six or seven times greater in the second stage of the 2SLS estimates than for OLS, and the confidence bands of the OLS estimates are within those of the 2SLS estimates for every single variable. Although these results do not in themselves validate OLS, they motivate its being preferable to 2SLS. Full details of these results are available on request. The most obvious candidates for instrumentation, factor prices, are not in the data set, so we used those constructed in Edwards & Behar (2006).

The generic IP procedure, implemented for Cobb Douglas production functions using panel data, involves two steps. The first step controls for the unobservables (I) by expressing value added in terms of the inputs and a non-parametric function of capital[13] and intermediate goods. The non-parametric function can be approximated by a polynomial, as done by Blalock & Gertler (2004). This step only requires terms at time t and can therefore be employed in a single cross-section. The second step requires information over multiple periods, which we do not have. Unlike Blalock & Gertler, we do need the second step to identify the capital coefficient and the higher order terms in capital, which is necessary for the calculation of all elasticities (cf equations (30), (33) and (34)).

We therefore modify the IP approach. We assume the production technology is a Cobb Douglas aggregation of capital and labor, where labor is a translog function of labor inputs. Borjas (2003) also imposes a Cobb Douglas restriction between capital and labor for identification purposes, nesting a CES structure within the labor types, but our restriction still allows sufficient flexibility within the labor inputs. In terms of equation (43), all $\beta_{ik} = 0$, where k is capital, such that capital is separable from the other inputs:

$$\log v = \log \alpha_0 + (\alpha_k \log x_k) + \left(\sum_i \alpha_i \log x_i + \frac{1}{2} \sum_i \sum_j \beta_{ij} \log x_i \log x_j \right) + \omega \tag{45}$$

The IP approach divides the error term such that $\omega = \mu + \phi(x_k, x_r)$, where ϕ is proxied by a second order polynomial in capital and raw materials. Thus, any terms in capital are exclusively capturing the unobservables I, not an underlying feature of the technology:

$$\log v = \log \alpha_0 + \left(\sum_i \alpha_i \log x_i + \frac{1}{2} \sum_i \sum_j \beta_{ij} \log x_i \log x_j \right) + \phi(x_k, x_r) + \mu \tag{46}$$

Provided the conditions in Levinsohn & Petrin (2003) hold, ϕ controls for I such that ω is orthogonal to the inputs. In (46), the coefficients on the capital terms are not identified. Recall the Cobb Douglas restriction implies $\beta_{kk} = 0$. Furthermore, we use the assumption of constant returns to scale ($\sum_i \alpha_i = 1$) to identify capital's contribution to output α_k and for use in elasticity calculations.

In summary, we will present baseline results assuming ω is orthogonal without additional variables. In addition, we will use control variables c to estimate (44), adapt the IP approach by including ϕ as in (46), or combine both. We will also include other terms, such as location and industry dummies and firm-specific variables relevant to the intercept, to improve the fit

[13] Capital differs from the other inputs on the assumption that the capital stock at time t was actually decided at $t-1$, while the other inputs are chosen at t conditional on the full information set.

of the model.

5.5 Inference

The elasticity estimates are non-linear combinations of the coefficients and data. Significant regression coefficients neither imply nor are necessary for significant elasticities (Anderson & Thursby, 1986), yet reviews of empirical work using translog functions make no mention of significance with respect to elasticities (Chung, 1994; Hamermesh, 1993). With respect to translog estimates of H and ϵ, Vere (2001) presents confidence intervals but assumes factor shares s are deterministic. We do allow for s to be stochastic by applying the "Delta" method, which calculates Taylor approximations to underlying distributions of functions of parameters to the elasticity estimates (Greene, 2003). The resulting p-values are a function of many paramaters, so precise estimates can be difficult to obtain. They can be sensitive to the distributions of the underlying parameters in finite samples and should be treated as indications only.

6 Disaggregated results

6.1 Regressions

This subsection discusses regression estimates of α and β in translog production functions, which form the basis of the elasticity calculations to follow. Unrestricted regressions (cf (27)) yielded returns to scale estimates of 1.06, which were insignificantly different from unity, suggesting upward bias from endogeneity is limited.[14] The results for disaggregated regressions with constant returns imposed are in Table A2. The first column only has the inputs and a constant. The overall fit is good and coefficients on all the higher order terms are jointly significant, rejecting the null hypothesis that the production technology is Cobb Douglas.[15] The results of separability tests permit us to proceed to more aggregated estimates, which are the subject of section 7.

Columns 2 and 3 are estimates of (44). A variable especially appropriate for inclusion in c is a measure of the firm's expected change in the product's price for the current period. On the assumption this expectation was formed at the start of the relevant period, it would provide a remedy to potential endogeneity bias. We also have a variable for the expected impact of new labor legislation. Other variables that may affect the production relationship

[14] Results are available on request.

[15] We are not referring to the Cobb Douglas restriction given by (45), but to a case where the whole production technology can be approximated by first order terms.

are dummies for owner-managed and large firms as well as the exports/sales ratio, which could be indicative of productivity. Industry and location dummies as well as information on recruitment and the training intensity of firms are included to help improve the fit of the regression. Computer investment intensity and the share of raw materials in costs provide further information used to improve the fit. However, they might inadvertently be playing an IP-type role, which would mean the capital coefficients are not correctly identified. Thus, column 2 has a full set of variables, while column 3 excludes these potential IP variables. In both columns 2 and 3, the sets of variables contribute explanatory power and reduce the mean square error (as well as the number of observations), but column 2 produces a better fit than column 3. Column 3 does not reject the hypothesis that all $\beta_{ij} = 0$, but column 2 does.

Column 4 repeats column 3 in terms of variables, but assumes a Cobb Douglas aggregation of capital and labor. It does not include proxies for ϕ but serves as a benchmark for comparison with columns 5 and 6. Column 5 estimates (46) using a quadratic in the capital stock and raw materials to proxy ϕ near the bottom of the table. Column 6 combines elements of c and ϕ along with additional variables.[16] We note that the Cobb Douglas aggregations in columns 4-6 do not lead to a material loss of fit, but joint tests on the β_{ij} terms are not significant. Joint tests of the IP terms are significant in columns 5 and 6, which in this model is consistent with the interpretation that the proxy variables are controlling for endogeneity.

6.2 Fully flexible wage elasticities

Table A3 presents the HEC estimates based on equations (30), (34) and (36). The columns match the regressions used to obtain the estimates of α and β in Table A2. The highlighted cell in column 1 suggests a 1% rise in the ratio of managerial/professional workers to unskilled workers would raise the ratio of unskilled to managerial/professional wages by 1.31% (the wage differential would fall). The first six rows describe the relationship between capital and the labor types: column 1 gives estimates that vary by occupation type and that vary from the elasticity of unity imposed by assumption in columns 4-6. A number of H_{ij} pairings can vary across specification. However, there are some consistent relationships. A relative rise in the quantity of managers/professionals would reduce the wage differential with respect to semi-skilled workers or unskilled workers.

[16] The term for raw materials as a share of costs is excluded. We experimented with including/excluding computer investment intensity and a number of different additional variables, either those appropriate for c or those simply likely to affect the intercept. They had no material impact on the results.

Table A3 introduces one of the key messages of this paper: while skilled/artisanal and unskilled workers are q-complements, semi-skilled and unskilled workers are q-substitutes. This difference would not have revealed itself with more restrictive functional forms or with more aggregated data. The result is of particular interest because it is the skills within the blue-collar occupations that enterprise-based training programs are trying to produce. We therefore focus our attention on these occupations when we consider elasticities of factor price.

Table A4 presents disaggregated elasticities of factor price, assuming all factor prices are perfectly flexible (cf equations (33) and (35)). The columns match the regressions from Table A2. The p-values are for two-sided tests of a null hypothesis that the elasticity is zero - that the factors are neither complements nor substitutes - calculated using the "Delta" method. Given the relatively low degrees of freedom in the regressions and the large numbers of parameters involved in the elasticity calculations, it is no surprise that many of the elasticities are insignificant. While low power is one explanation, another is simply that there is no clear relationship between some of the inputs - they are neither strong complements nor substitutes.

The assumption of perfectly elastic product market demand could be justified given that South Africa is a small open economy. Nonetheless, if product demand elasticities are finite, the implied wage effects will be too positive, so some factor pairs indicated to be complements may be substitutes. We therefore include present values of $|\eta^*|$. The more inelastic product demand must be, the less likely it is that we are incorrectly predicting two factors are q-complements. For $\epsilon_{ij} < 0$, $\eta^* > 0$, so the calculation is not shown.

The highlighted entry in column 1 indicates that a 10% rise in the supply of skilled/artisanal workers would raise unskilled wages by 7.3%. The p-value is 0.02 and demand would have to be a very inelastic $|\eta| < 0.13$ for this positive wage effect to be a negative one. A rise in the supply of semi-skilled labor would lower unskilled wages by 8.5% with a p-value of 0.06. Columns 1-3 all yield consistently statistically significant results: a rise in the supply of skilled/artisanal workers would raise unskilled wages while a rise in the supply of semi-skilled workers would reduce unskilled wages. The coefficients in columns 4-6 re-enforce our message. The calculations based on IP regressions in columns 5 and 6 also tend to produce higher own-elasticities of factor price. Column 6 produces the highest cross elasticities of factor price ($+1.04$ and -1.71 for skilled/artisanal and semi-skilled workers respectively). However, the Cobb Douglas restriction generally reduces the precision of the estimates and raises p-values.

6.3 Rigid Wages

Table A5 presents elasticities of factor price but allows for the unskilled wage to be rigid (cf equation (25)). There are few changes when compared to Table A4, but a notable exception is the peculiar case of semi-skilled workers: a rise in their supply would raise semi-skilled wages.[17]Furthermore, the additional parameters used to calculate the elasticity make them less precise.

The bottom portion of Table A5 presents the employment response of unskilled workers to changes in the quantities of other workers (equation (24)). In column 1, the highlighted statistic indicates a 10% rise in the supply of managers/professionals would raise unskilled employment by 6.7%. Column 1 also preserves our findings within the blue collar occupations: a rise in skilled/artisanal labor would raise unskilled employment while a rise in semi-skilled labor would reduce unskilled employment.

The employment responses in column 3 are large, which is a result of the low own-elasticity of factor price calculated in Table A4.[18] Columns 5 and 6 produce more moderate unskilled employment responses: despite producing higher elasticities of factor price for skilled/artisanal workers in Table A4, the high own-elasticities of factor price yield employment elasticities of $0.52 - 0.57$ in Table A5. Similarly, despite generating higher elasticities of factor price for semi-skilled workers, the unskilled employment response to semi-skilled workers is between -0.93 and -1.06.

In summary, with the caveat that the estimates are not precise, this section has suggested that a rise in the supply of skilled/artisanal workers would raise demand for unskilled labor while a rise in the supply of semi-skilled workers would reduce demand for unskilled labor. This is completely consistent with our earlier findings.

7 Aggregate results

7.1 Regressions

It is common for "skilled" and "unskilled" labor to be proxied by white and blue collar workers (Hamermesh, 1993). To relate our results to that literature and to get a more aggregate

[17]Equation (25) shows this is more likely for factor $i = j$ if the technology is such that, with completely flexible wages, the own elasticities of factors i and u are low, and the two factors are large complements or large substitutes.

[18]The intuition for this is that a rise in the supply of, say, skilled/artisanal workers would shift the labor demand curve out and to the right. The own-elasticity in Table A4 indicates the marginal product of unskilled labor is diminishing slowly (the labor demand curve is relatively flat at the firm level). As a result, for a given fixed unskilled wage, the employment increase is large.

sense of complementarities between these types, we combine the Managerial/Professional and Sales/Clerical groups to form a white collar aggregate and add skilled/artisanal, semi-skilled and unskilled workers to form a blue collar aggregate. This common practice can be problematic because many blue collar workers are more skilled than sales/clerical workers. Nonetheless, we present the results in Table A6. Column 1 has no additional variables. Column 2 includes the firm's expected price changes, expected labor legislation impact and a number of other variables, but does not include potential investment indicators. Column 3 includes a full set of additional variables. Column 4 presents the IP procedure with no additional variables.[19]

7.2 Elasticities

Table A7 contains aggregate HECs. By finding that capital and blue collar workers are q-substitutes while capital and white collar workers are q-complements, columns 1-3 produce results consistent with Capital Skill Complementarity: a rise in the capital stock benefits skilled workers more than unskilled workers (Krusell et al, 2000).[20] These results are robust across our aggregate (non-IP) specifications, but they do not reflect patterns seen for the disaggregated results. Capital is by assumption q-complementary with both blue and white collar workers in column 4. While unity is close to the estimated elasticity with respect to white collar workers in columns 1 and 2, it is quite different to the elasticity with respect to blue collar workers and is therefore a relatively stringent restriction to place on the data.

Columns 1-3 indicate blue and white collar labor are q-complements with similar coefficients: a 1% rise in the ratio of white to blue collar workers would reduce the wage premium by $1.55 - 1.76\%$. Because the term in brackets in equation (45) is effectively a two-input production translog, the labor terms are necessarily q-complements in column 4. Imposing the Cobb Douglas aggregation with no IP did not in itself change the elasticity, yielding a value of 1.66, but our use of proxies for ϕ generates a higher estimate of 2.88.

A good number of the elasticities of factor price presented in Table A8 are significant. In column 1, a 1% rise in the supply of white collar workers would lead to a 0.98% rise in blue collar wages. The elasticity of approximately unity is found across all four specifications. Furthermore, $|\eta^*| \approx 0.6$ in columns 1-3, which is quite inelastic, while the IP specification yields a more inelastic threshold of 0.35 in column 4. It is therefore likely that a rise in white collar workers would raise blue collar wages, even if product demand is finitely elastic.

[19] The coefficient symmetry visible in column 4 is a result of the restrictions imposed (cf equation (27), where there are three inputs and $\beta_{kk} = 0$).

[20] Capital Skill Complementarity, together with extensive capital deepening, is one of many explanations offered for observed rises in wage inequality between skilled and unskilled workers.

While the own-elasticity of factor price for blue collar labor is about -0.9 in columns 1-3, the IP regression yields an own-elasticity of -1.5. Hence, adjusting for rigid blue collar wages produces some variation in employment elasticities ρ_{ij}. In column 4, a 1% rise in white collar workers leads to a 0.69% rise in blue collar employment, while it leads to an employment rise to the order of 1% in columns 1-3.

In summary, a rise in the supply of white collar labor would raise demand for blue collar labor.

8 Conclusion

> *"Yet both unemployment and poverty are still at unacceptably high levels, which mean our growth is not fairly shared. The most fatal constraint to shared growth is skills, and it should be noted that skills are not just one of the constraints facing AsgiSA but a potentially fatal constraint. That fact should be admitted with emphasis."* - South African Deputy President, Phumzile Mlambo-Ngcuka (2006), at the launch of the Joint Initiative for Priority Skills Acquisition (JIPSA), which is part of the government's Accelerated and Shared Growth Initiative for South Africa (AsgiSA).

The very name *AsgiSA* makes clear the intention that improvements in living standards are to be shared by all segments of society, in particular the poor. Implicit in the argument for the role of JIPSA in AsgiSA is the claim that improved access to education and training, which would equip a portion of the population with skills, will generate enough growth in a way that benefits those who do not acquire those skills.

Our aggregate findings are supportive of this view: The Hicks Elasticity of Complementarity between blue and white collar workers is about 1.7. We find elasticities of factor price of about unity and employment elasticities of about unity also. To summarize our disaggregated findings, the median[21] elasticity of factor price we calculated indicates a 1% rise in the supply of semi-skilled workers would reduce unskilled wages by 1.1% while a rise in skilled/artisanal workers would raise unskilled wages by 0.76%. Adjusting for rigid wages, the median unskilled employment elasticities are -1.73 for semi-skilled workers and 1.5 for skilled/artisanal workers.

If our results for manufacturing are representative of the broader economy, they have the following implications. Given that the ratio of blue:white collar workers in our data set is about 4:1, our aggregate findings mean that equipping 2% of blue collar workers for white

[21] We excluded the pure Cobb Douglas aggregation (column 4) from this calculation.

collar jobs would reduce the white:blue collar wage premium by 17%. Our disaggregated findings imply addressing the shortage of artisans would raise unskilled employment and/or wages. The mechanisms at play are that skilled/artisanal workers permit additional output, which raises demand for all factors including unskilled labor, and that skilled/artisanal workers make unskilled workers more productive.

However, trade union officials claim it is only so-called soft skills which are being provided by firms so that they can reclaim their skills levy and prospective artisans make up a low proportion of those being trained (Paton, 2003; Ntuli, 2006). By producing the "wrong" skills, these training programs may raise unskilled unemployment.

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	Sales (Rm)	Value Added (Rm)	Capital (Rm)	Managerial/Professional	Sales/ Clerical	Skilled/ Artisanal	Semi-skilled	Unskilled
mean	110	48	51	22	40	27	120	87
median	13	7	5	5	6	5	19	14
p25	5	3	1.5	2	2	1	5	4
p75	50	24	21	11	20	15	68	50

Table A1: Basic Descriptive Statistics of output and factor inputs.

	1: nocontrol		2: full		3: pure	
	coefficient	se	coefficient	se	coefficient	se
Capital	0.27***	0.06	0.18***	0.054	0.18**	0.067
Man/Prof	0.20**	0.096	0.11	0.1	0.2	0.13
Sale/Cler	0.22**	0.09	0.41***	0.082	0.27***	0.1
Skil/Art	0.056	0.062	-0.041	0.068	0.11	0.078
Semi	0.098	0.068	0.13**	0.065	0.11	0.079
Un	0.16***	0.056	0.21***	0.051	0.14**	0.062
0.5*Capital²	0.059	0.038	0.083**	0.036	0.032	0.043
Capital*Man/Prof	-0.0053	0.049	-0.05	0.042	0.013	0.052
Capital*Sale/Cler	-0.0054	0.047	0.045	0.042	0.041	0.051
Capital*Skil/Art	0.024	0.034	-0.034	0.033	-0.026	0.04
Capital*Semi	-0.014	0.037	-0.031	0.032	-0.004	0.039
Capital*Un	-0.058**	0.028	-0.013	0.026	-0.057*	0.031
0.5*Man/Prof²	0.053	0.099	0.031	0.099	-0.01	0.12
Man/Prof*Sale/Cler	-0.1	0.085	-0.052	0.074	-0.078	0.091
Man/Prof*Skil/Art	-0.01	0.056	-0.023	0.056	0.02	0.068
Man/Prof*Semi	0.055	0.055	0.029	0.051	0.0037	0.064
Man/Prof*Un	0.0085	0.051	0.064	0.046	0.051	0.057
0.5*Sale/Cle²	0.094	0.094	0.09	0.083	0.092	0.1
Sale/Cler*Skil/Art	-0.025	0.054	-0.026	0.052	-0.052	0.064
Sale/Cler*Semi	0.0011	0.053	-0.013	0.048	0.027	0.059
Sale/Cler*Un	0.037	0.041	-0.045	0.041	-0.031	0.051
0.5*Skil/Art²	-0.057	0.053	-0.059	0.059	-0.038	0.07
Skil/Art*Semi	-0.00078	0.038	0.064*	0.039	0.035	0.043
Skil/Art*Un	0.069**	0.033	0.078**	0.036	0.06	0.044
0.5*Semi²	0.059	0.05	0.066	0.047	0.039	0.054
Semi*Un	-0.10***	0.034	-0.12***	0.034	-0.10**	0.042
0.5*Un²	0.044	0.036	0.03	0.042	0.079	0.051
ind2			0.29*	0.17	0.052	0.2
ind3			0.17	0.17	-0.01	0.21
ind4			0.60***	0.16	0.43**	0.19
ind5			0.12	0.17	-0.13	0.2
ind6			0.19	0.18	-0.056	0.21
ind7			0.26	0.16	0.08	0.19
ind8			0.086	0.18	-0.089	0.21
ind9			0.24	0.16	0.13	0.19
loc2			0.26	0.26	0.31	0.33
loc3			0.15	0.12	0.13	0.15
loc4			0.23*	0.12	0.13	0.15
loc5			0.2	0.3	0.29	0.38
loc6			-0.38	0.39	-0.26	0.48
loc7			-0.92**	0.39	-1.06**	0.49
loc8			-0.27	0.35	-0.39	0.44
loc9			0.15	0.12	0.13	0.14
Exports/Sales			0.31	0.19	0.52**	0.24
Expected Price Change			0.0069**	0.0031	0.011***	0.0038
Raw materials / Costs			-0.016***	0.0018		
Ease of recruitment Man/Prof			0.053	0.066	0.016	0.081
Ease of recruitment Sale/Cler			0.1	0.065	0.19**	0.077
Ease of recruitment Skil/Art			-0.015	0.058	-0.0086	0.071
Ease of recruitment Semi			0.02	0.065	0.071	0.078
Ease of recruitment Un			0.095	0.1	-0.076	0.12
Training/Sales			-0.0038***	0.0011	-0.0015	0.0013
Impact of Labor Legislation			0.026**	0.012	0.011	0.014
Large Firm			0.50***	0.092	0.42***	0.11
Computer Investment / Assets			2.86***	0.98		
Ownermanaged			0.48***	0.17	0.65***	0.2
Constant	-0.0089	0.09	-1.13***	0.35	-1.14***	0.43
N		299		218		224
Root Mean Square Error		0.65		0.46		0.57
R^2		0.92		0.96		0.93
Joint test on all β_{ij}=0		0.08		0.02		0.67
Aggregate white collar		0.92		0.83		0.95
Aggregate blue collar		0.62		0.51		0.77

Table A2: Disaggregated regressions. *, ** & *** denote significance at 10%, 5% & 1%; dependent variable is Value Added. Column 1 has the inputs and a constant; column 2 has a full set of controls; column 3 omits potential investment indicators.

	4: cd		5: nocon		6: all	
	coefficient	se	coefficient	se	coefficient	se
Capital	0.11***	0.039				
Man/Prof	0.23*	0.12	0.20**	0.099	0.17	0.12
Sale/Cler	0.27***	0.095	0.064	0.08	0.18*	0.093
Skil/Art	0.13*	0.076	0.095*	0.057	0.029	0.077
Semi	0.11	0.077	0.095	0.059	0.12*	0.074
Un	0.15**	0.06	0.14***	0.044	0.21***	0.056
0.5*Man/Prof^2	0.00044	0.12	0.074	0.085	0.04	0.11
Man/Prof*Sale/Cler	-0.047	0.089	-0.12*	0.068	-0.08	0.083
Man/Prof*Skil/Art	0.015	0.066	0.0089	0.049	-0.018	0.062
Man/Prof*Semi	-0.003	0.063	0.03	0.048	-0.015	0.055
Man/Prof*Un	0.035	0.054	0.011	0.041	0.072	0.05
0.5*Sale/Cle^2	0.079	0.1	0.087	0.081	0.063	0.092
Sale/Cler*Skil/Art	-0.041	0.062	-0.037	0.044	-0.047	0.059
Sale/Cler*Semi	0.027	0.058	0.025	0.042	0.045	0.054
Sale/Cler*Un	-0.018	0.047	0.049	0.032	0.019	0.042
0.5*Skil/Art^2	-0.053	0.069	0.0087	0.046	-0.03	0.065
Skil/Art*Semi	0.04	0.042	-0.0089	0.032	0.047	0.043
Skil/Art*Un	0.039	0.04	0.028	0.026	0.048	0.037
0.5*Semi^2	0.033	0.054	0.026	0.042	0.016	0.053
Semi*Un	-0.098**	0.04	-0.072**	0.028	-0.093**	0.038
0.5*Un^2	0.041	0.047	-0.016	0.03	-0.046	0.047
ind2	0.12	0.19			-0.022	0.19
ind3	0.034	0.2			-0.052	0.2
ind4	0.48**	0.18			0.42**	0.18
ind5	-0.077	0.2			-0.14	0.19
ind6	-0.0081	0.21			0.18	0.19
ind7	0.13	0.19			0.024	0.18
ind8	-0.016	0.21			-0.03	0.19
ind9	0.16	0.19			0.098	0.17
loc2	0.26	0.32			0.50*	0.28
loc3	0.15	0.15			0.14	0.14
loc4	0.14	0.15			0.14	0.14
loc5	0.26	0.37			0.19	0.36
loc6	-0.24	0.48			-0.16	0.61
loc7	-0.96**	0.48			-0.88**	0.44
loc8	-0.49	0.43			-0.11	0.33
loc9	0.13	0.14			0.14	0.14
Exports/Sales	0.55**	0.24			0.72***	0.22
Expected Price Change	0.010***	0.0037			0.0084**	0.0034
Ease of recruitment Man/Prof	0.022	0.079			0.1	0.078
Ease of recruitment Sale/Cler	0.17**	0.076			-0.012	0.073
Ease of recruitment Skil/Art	-0.024	0.069			-0.068	0.064
Ease of recruitment Semi	0.071	0.078			0.11	0.078
Ease of recruitment Un	-0.061	0.12			-0.09	0.11
Training/Sales	-0.0020*	0.0012			-0.0024*	0.0012
Impact of Labor Legislation	0.0099	0.014			-0.0056	0.013
Large Firm	0.45***	0.11			0.41***	0.14
Computer Investment / Assets					3.78***	1.1
Ownermanaged	0.65***	0.2			0.55***	0.2
Stock of Capital			0.35*	0.18	-0.15	0.23
Raw			0.14	0.25	0.4	0.31
Raw^2			0.014	0.023	-0.03	0.029
Stock*Raw			-0.047	0.034	0.048	0.048
Stock^2			0.035**	0.016	-0.0084	0.023
Constant	-1.12***	0.42	-1.03	0.68	-1.69*	0.89
N		224		328		226
Root Mean Square Error		0.57		0.58		0.52
R^2		0.93		0.94		0.96
Joint test on all β_{ij}=0		0.67		0.15		0.13
Aggregate white collar		0.98		0.33		0.32
Aggregate blue collar		0.98		0.33		0.32
Joint test on LP terms		.		0		0.11

Table A2 (cont.): Column 4 has no IP terms and excludes potential investment indicators; column 2 has IP terms but no other variables; column 3 has IP terms and other variables.

$H_{ij}=H_{ji}$ i	j	1:nocontrol	2:full	3:pure	4:cd	5:nocon	6:all
Capital	Capital	-2.68	-1.42	-5.58	-7.83	-1.45	-2.56
	Man/Prof	0.89	-1.12	1.52	1	1	1
	Sale/Cler	0.9	2.1	2.4	1	1	1
	Skil/Art	2.31	-1.75	-0.25	1	1	1
	Semi	-0.03	-1.2	0.52	1	1	1
	Un	-1.88	-0.16	-4.09	1	1	1
Man/Prof	Capital	0.89	-1.12	1.52	1	1	1
	Man/Prof	-2.14	-3.15	-3.37	-2.96	-2.1	-3.05
	Sale/Cler	-0.41	0.29	-0.17	0.37	-2.44	-0.49
	Skil/Art	0.59	-0.03	1.44	1.31	1.4	0.25
	Semi	4.06	2.15	1.2	0.85	3.48	0.05
	Un	1.31	4.34	3.04	2.99	2.01	8.01
Sale/Cler	Capital	0.9	2.1	2.4	1	1	1
	Man/Prof	-0.41	0.29	-0.17	0.37	-2.44	-0.49
	Sale/Cler	-1.35	-1.1	-1.4	-1.48	-1.88	-1.83
	Skil/Art	0.1	0.32	0.03	0.27	-1.06	-0.45
	Semi	1.05	0.72	2.26	2.16	3.55	3.09
	Un	2.18	-0.35	-0.06	0.12	6.54	2.37
Skil/Art	Capital	2.31	-1.75	-0.25	1	1	1
	Man/Prof	0.89	-1.12	1.52	1.31	1.4	0.25
	Sale/Cler	0.9	2.1	2.4	0.27	-1.06	-0.45
	Skil/Art	-15.26	-13.33	-5.22	-5.74	-7.81	-9.39
	Semi	0.89	5.8	3.36	3.63	-0.51	5.9
	Un	7.51	8.69	3.95	3.98	6.24	8.7
Semi	Capital	-0.03	-1.2	0.52	1	1	1
	Man/Prof	4.06	2.15	1.2	0.85	3.48	0.05
	Sale/Cler	1.05	0.72	2.26	2.16	3.55	3.09
	Skil/Art	0.89	5.8	3.36	3.63	-0.51	5.9
	Semi	-1.35	-2.79	-5.37	-6.32	-8.54	-9.04
	Un	-11.93	-8.88	-11.38	-16.6	-23.53	-21.57
Un	Capital	-1.88	-0.16	-4.09	1	1	1
	Man/Prof	1.31	4.34	3.04	2.99	2.01	8.01
	Sale/Cler	2.18	-0.35	-0.06	0.12	6.54	2.37
	Skil/Art	7.51	8.69	3.95	3.98	6.24	8.7
	Semi	-11.93	-8.88	-11.38	-16.6	-23.53	-21.57
	Un	-4.46	-6.2	-1.4	-4.8	-24.53	-35.22

Table A3: Disaggregated Hicks Elasticities of Complementarity based on regressions in Table A2. While skilled/artisanal and unskilled workers are q-complements, semi-skilled and unskilled workers are q-substitutes.

	ε_{ij}	1: nocontrol			2: full			3: pure		
i	j	Estimate	p value	η*	Estimate	p value	η*	Estimate	p value	η*
Capital	Capital	-0.5	0.02	.	-0.17	0.7	.	-0.59	0.18	.
	Man/Prof	0.22	0.38	1.13	-0.23	0.55	.	0.36	0.44	0.66
	Sale/Cler	0.26	0.29	1.11	0.752	0.04	0.48	0.7	0.17	0.42
	Skil/Art	0.23	0.22	0.43	-0.19	0.52	.	-0.05	0.9	.
	Semi	-0.003	0.99	.	-0.15	0.6	.	0.04	0.91	1.94
	Un	-0.21	0.17	.	-0.02	0.95	.	-0.43	0.21	.
Man/Prof	Capital	0.16	0.41	1.13	-0.13	0.52	.	0.19	0.49	0.66
	Man/Prof	-0.54	0.17	.	-0.64	0.19	.	-0.8	0.14	.
	Sale/Cler	0.12	0.73	.	0.1	0.78	3.5	-0.05	0.9	.
	Skil/Art	0.06	0.8	1.69	-0.003	0.99	.	0.28	0.33	0.7
	Semi	0.29	0.19	0.25	0.26	0.3	0.47	0.09	0.72	0.83
	Un	0.14	0.48	0.76	0.41	0.08	0.23	0.32	0.19	0.33
Sale/Cler	Capital	0.17	0.33	1.11	0.24	0.08	0.48	0.25	0.21	0.42
	Man/Prof	-0.1	0.73	.	0.06	0.78	3.5	-0.04	0.9	.
	Sale/Cler	-0.39	0.25	.	-0.39	0.09	.	-0.39	0.29	.
	Skil/Art	0.01	0.96	10.4	0.03	0.82	3.15	0.01	0.98	31.7
	Semi	0.07	0.69	0.95	0.09	0.53	1.4	0.18	0.41	0.44
	Un	0.23	0.11	0.46	-0.03	0.79	.	-0.01	0.97	.
Skil/Art	Capital	0.43	0.27	0.43	-0.2	0.51	.	-0.03	0.9	.
	Man/Prof	0.15	0.8	1.69	-0.005	0.99	.	0.34	0.37	0.7
	Sale/Cler	0.03	0.96	10.4	0.11	0.82	3.15	0.09	0.98	31.7
	Skil/Art	-1.49	0.03	0.07	-1.44	0.03	.	-1	0.01	.
	Semi	0.06	0.88	1.13	0.72	0.13	0.17	0.26	0.31	0.3
	Un	0.82	0.08	0.13	0.82	0.06	0.12	0.42	0.11	0.25
Semi	Capital	-0.01	0.99	.	-0.14	0.58	.	0.05	0.91	1.94
	Man/Prof	1.02	0.32	0.25	0.44	0.33	0.47	0.29	0.73	0.83
	Sale/Cler	0.3	0.69	0.95	0.25	0.52	1.4	0.63	0.45	0.44
	Skil/Art	0.09	0.87	1.13	-0.63	0.05	0.17	0.65	0.24	0.3
	Semi	-0.1	0.9	.	-0.35	0.35	.	-0.42	0.54	.
	Un	-1.31	0.19	.	-0.83	0.06	.	-1.2	0.28	.
Un	Capital	-0.35	0.15	.	-0.02	0.94	.	-0.44	0.13	.
	Man/Prof	0.33	0.49	0.76	0.89	0.14	0.23	0.73	0.25	0.33
	Sale/Cler	0.62	0.12	0.46	-0.13	0.79	.	-0.02	0.97	.
	Skil/Art	0.73	0.02	0.13	0.94	0.03	0.12	0.76	0.06	0.25
	Semi	-0.85	0.06	.	-1.1	0.05	.	-0.89	0.1	.
	Un	-0.49	0.14	.	-0.59	0.18	.	-0.15	0.76	.

Table A4: Elasticities of factor price and associated values of η* based on regressions in Table A2. A 1% rise in the supply of skilled/artisanal workers would raise unskilled wages by 0.73-0.94% while a 1% rise in the supply of semi-skilled workers would reduce unskilled wages by 0.85-1.1%. Column 3 has a low own-elasticity of factor price for unskilled labor (-0.15).

ε_{ij}		4: cd			5: nocon			6: all		
i	j	Estimate	p value	η*	Estimate	p value	η*	Estimate	p value	η*
Capital	Capital	-0.89	0	.	-0.59	0	.	-0.72	0	.
	Man/Prof	0.25	0	1	0.21	0	1	0.2	0.001	1
	Sale/Cler	0.3	0	1	0.17	0.001	1	0.27	0	1
	Skil/Art	0.19	0	1	0.1	0.004	1	0.12	0.01	1
	Semi	0.08	0.12	1	0.06	0.11	1	0.08	0.11	1
	Un	0.07	0.09	1	0.05	0.09	1	0.05	0.18	1
Man/Prof	Capital	0.11	0.004	1	0.41	0	1	0.28	0.002	1
	Man/Prof	-0.75	0.13	.	-0.44	0.27	.	-0.6	0.29	.
	Sale/Cler	0.11	0.76	2.72	-0.42	0.18	.	-0.13	0.74	.
	Skil/Art	0.25	0.34	0.76	0.15	0.53	0.71	0.03	0.92	3.95
	Semi	0.07	0.78	1.17	0.2	0.39	0.29	0.004	0.99	16.4
	Un	0.21	0.32	0.33	0.1	0.59	0.5	0.42	0.14	0.12
Sale/Cler	Capital	0.11	0.004	1	0.41	0	1	0.28	0.002	1
	Man/Prof	0.09	0.75	2.72	-0.51	0.25	.	-0.1	0.75	.
	Sale/Cler	-0.44	0.2	.	-0.32	0.52	.	-0.5	0.14	.
	Skil/Art	0.05	0.82	3.74	-0.11	0.69	.	-0.05	0.81	.
	Semi	0.17	0.37	0.46	0.2	0.43	0.28	0.25	0.21	0.32
	Un	0.01	0.96	8.4	0.34	0.12	0.15	0.12	0.43	0.42
Skil/Art	Capital	0.11	0.004	1	0.41	0	1	0.28	0.002	1
	Man/Prof	0.33	0.37	0.76	0.3	0.54	0.71	0.05	0.93	3.95
	Sale/Cler	0.08	0.82	3.74	-0.18	0.68	.	-0.12	0.81	.
	Skil/Art	-1.09	0.01	.	-0.81	0.07	.	-1.13	0.06	.
	Semi	0.29	0.26	0.28	-0.03	0.93	.	0.47	0.27	0.17
	Un	0.28	0.24	0.25	0.32	0.27	0.16	0.45	0.21	0.12
Semi	Capital	0.11	0.004	1	0.41	0	1	0.28	0.002	1
	Man/Prof	0.22	0.79	1.17	0.73	0.45	0.29	0.01	0.99	19.4
	Sale/Cler	0.64	0.43	0.46	0.61	0.46	0.28	0.84	0.32	0.32
	Skil/Art	0.69	0.2	0.28	-0.06	0.93	.	0.71	0.19	0.17
	Semi	-0.5	0.44	.	-0.49	0.52	.	-0.72	0.27	.
	Un	-1.15	0.21	.	-1.21	0.17	.	-1.12	0.27	.
Un	Capital	0.11	0.004	1	0.41	0	1	0.28	0.002	1
	Man/Prof	0.75	0.41	0.33	0.42	0.61	0.5	1.57	0.31	0.12
	Sale/Cler	0.04	0.96	8.4	1.12	0.2	0.15	0.65	0.45	0.42
	Skil/Art	0.75	0.2	0.25	0.65	0.2	0.16	1.04	0.21	0.11
	Semi	-1.32	0.17	.	-1.34	0.17	.	-1.71	0.24	.
	Un	-0.33	0.63		-1.26	0.05	.	-1.84	0.13	.

Table A4 (cont.): A 1% rise in the supply of skilled/artisanal workers would raise unskilled wages by 0.65-1.04% while a 1% rise in the supply of semi-skilled workers would reduce unskilled wages by 1.32-1.71%. Column 6 has a high own-elasticity of factor price for unskilled labor (-1.84).

ε^{ρ}_{ij}		1: nocontrol		2: full		3: pure	
i	j	Estimate	p value	Estimate	p value	Estimate	p value
Capital	Capital	-0.35	0.35	-0.16	0.71	0.68	0.89
	Man/Prof	0.08	0.83	-0.25	0.61	-1.75	0.82
	Sale/Cler	-0.01	0.99	0.75	0.05	0.72	0.68
	Skil/Art	-0.08	0.82	-0.21	0.64	-2.27	0.77
	Semi	0.35	0.47	-0.12	0.82	2.63	0.79
Man/Prof	Capital	0.06	0.84	-0.14	0.58	-0.78	0.82
	Man/Prof	-0.44	0.38	-0.02	0.98	0.77	0.9
	Sale/Cler	0.07	0.86	0.01	0.98	-0.08	0.95
	Skil/Art	0.27	0.43	0.65	0.33	1.93	0.73
	Semi	0.04	0.94	-0.5	0.58	-1.83	0.8
Sale/Cler	Capital	-0.004	0.99	0.24	0.08	0.27	0.69
	Man/Prof	0.06	0.86	0.01	0.98	-0.08	0.95
	Sale/Cler	-0.08	0.85	-0.38	0.13	-0.39	0.32
	Skil/Art	0.37	0.29	0.02	0.94	-0.03	0.98
	Semi	-0.37	0.41	0.12	0.72	0.18	0.88
Skil/Art	Capital	-0.16	0.82	-0.23	0.63	-1.25	0.77
	Man/Prof	0.7	0.45	1.24	0.33	2.39	0.73
	Sale/Cler	1.08	0.31	-0.06	0.94	-0.04	0.98
	Skil/Art	-0.26	0.81	-0.12	0.93	1.14	0.87
	Semi	-1.36	0.32	-0.82	0.62	-2.24	0.8
Semi	Capital	0.93	0.51	-0.11	0.82	3.6	0.79
	Man/Prof	0.14	0.94	-0.83	0.59	-5.61	0.8
	Sale/Cler	-1.36	0.51	0.43	0.63	0.77	0.86
	Skil/Art	-1.87	0.42	-0.72	0.64	-5.54	0.81
	Semi	2.17	0.52	1.23	0.56	6.8	0.81
ρ_{uj}		Estimate	p value	Estimate	p value	Estimate	p value
Un	Capital	-0.71	0.36	-0.03	0.95	-2.94	0.78
	Man/Prof	0.67	0.53	1.52	0.3	4.91	0.78
	Sale/Cler	1.28	0.24	-0.22	0.81	-0.11	0.97
	Skil/Art	1.5	0.17	1.61	0.23	5.15	0.77
	Semi	-1.73	0.3	-1.89	0.31	-6	0.78

Table A5: Elasticities of factor price wth rigid unskilled wages. A rise in skilled/artisanal labor would raise unskilled employment while a rise in semi-skilled labor would reduce unskilled employment.

ε^{ρ}_{ij}		4: cd		5: nocon		6: all	
i	j	Estimate	p value	Estimate	p value	Estimate	p value
Capital	Capital	-0.86	0	-0.58	0	-0.71	0
	Man/Prof	0.41	0.25	0.23	0.001	0.24	0.004
	Sale/Cler	0.3	0.06	0.22	0	0.29	0
	Skil/Art	0.35	0.3	0.13	0.004	0.15	0.01
	Semi	-0.2	0.76	0.002	0.97	0.03	0.63
Man/Prof	Capital	0.18	0.27	0.44	0	0.34	0.003
	Man/Prof	-0.28	0.85	-0.4	0.31	-0.24	0.72
	Sale/Cler	0.13	0.82	-0.33	0.31	0.01	0.98
	Skil/Art	0.72	0.51	0.2	0.41	0.27	0.43
	Semi	-0.76	0.74	0.09	0.8	-0.38	0.46
Sale/Cler	Capital	0.12	0.08	0.52	0	0.3	0.001
	Man/Prof	0.11	0.82	-0.4	0.37	0.01	0.98
	Sale/Cler	-0.44	0.18	-0.02	0.97	-0.45	0.15
	Skil/Art	0.07	0.86	0.06	0.83	0.02	0.95
	Semi	0.11	0.87	-0.18	0.67	0.1	0.69
Skil/Art	Capital	0.21	0.32	0.51	0	0.35	0.005
	Man/Prof	0.96	0.51	0.4	0.41	0.44	0.45
	Sale/Cler	0.11	0.87	0.1	0.84	0.04	0.95
	Skil/Art	-0.46	0.77	-0.65	0.13	-0.87	0.17
	Semi	-0.81	0.77	-0.37	0.44	0.05	0.94
Semi	Capital	-0.28	0.93	0.02	0.96	0.11	0.57
	Man/Prof	-2.4	0.74	0.33	0.81	-0.95	0.46
	Sale/Cler	0.52	0.84	-0.47	0.71	0.45	0.62
	Skil/Art	-1.92	0.77	-0.68	0.53	0.07	0.94
	Semi	4.1	0.75	0.8	0.69	0.33	0.84
ρ_{uj}		Estimate	p value	Estimate	p value	Estimate	p value
Un	Capital	0.34	0.64	0.32	0.04	0.15	0.11
	Man/Prof	2.26	0.68	0.34	0.6	0.86	0.19
	Sale/Cler	0.11	0.96	0.89	0.18	0.35	0.41
	Skil/Art	2.26	0.66	0.52	0.21	0.57	0.21
	Semi	-3.97	0.69	-1.06	0.23	-0.93	0.25

Table A5 (cont.): Columns 5-6 produce more moderate values of ρ_{uj} than columns 1-3.

	1: nocon		2: pure		3: all		4: lpnocon	
	coefficient	se	coefficient	se	coefficient	se	coefficient	se
Capital	0.35***	0.086	0.28***	0.091	0.31***	0.075		
White	0.43***	0.097	0.49***	0.12	0.49***	0.098	0.21**	0.086
Blue	0.22*	0.12	0.23	0.15	0.20*	0.12	0.35***	0.085
0.5*Capital^2	0.064	0.039	0.059	0.043	0.11***	0.037		
Capital*white	0.0033	0.041	0.0063	0.047	-0.05	0.04		
Capital*blue	-0.067	0.041	-0.065	0.045	-0.056	0.037		
05*White^2	-0.11	0.068	-0.11	0.08	-0.03	0.066	-0.13**	0.054
White*blue	0.10*	0.061	0.099	0.077	0.08	0.064	0.13**	0.054
0.5*Blue^2	-0.037	0.071	-0.034	0.092	-0.024	0.076	-0.13**	0.054
ind2			0.015	0.18	0.32**	0.15		
ind3			-0.098	0.19	0.14	0.16		
ind4			0.41**	0.18	0.61***	0.16		
ind5			-0.026	0.19	0.24	0.16		
ind6			-0.15	0.19	0.16	0.17		
ind7			0.17	0.18	0.33**	0.16		
ind8			0.042	0.2	0.2	0.17		
ind9			0.19	0.19	0.31**	0.16		
loc2			0.38	0.32	0.27	0.26		
loc3			0.15	0.15	0.16	0.12		
loc4			0.21	0.15	0.28**	0.12		
loc5			0.37	0.37	0.25	0.31		
loc6			0.085	0.48	-0.12	0.39		
loc7			-1.32***	0.47	-1.21***	0.39		
loc8			-0.34	0.4	-0.26	0.33		
loc9			0.15	0.14	0.14	0.12		
Exports/Sales			0.47**	0.22	0.26	0.19		
Expected Price Change			0.0087**	0.0037	0.0063**	0.0031		
Ease of recruitment Man/Prof			0.023	0.08	0.056	0.067		
Ease of recruitment Sale/Cler			0.15*	0.076	0.1	0.064		
Ease of recruitment Skil/Art			-0.029	0.069	-0.02	0.058		
Ease of recruitment Semi			0.086	0.077	0.0023	0.066		
Ease of recruitment Un			-0.06	0.12	0.12	0.099		
Training/Sales			-0.0014	0.0013	-0.0034***	0.0011		
Impact of Labor Legislation			0.016	0.014	0.027**	0.012		
Large Firm			0.37***	0.099	0.52***	0.085		
Ownermanaged			0.63***	0.19	0.44***	0.16		
Raw materials / Costs					-0.016***	0.0018		
Computer Investment / Assets					2.16**	0.95		
Stock of capital							0.40**	0.18
Raw							0.032	0.24
Raw^2							0.023	0.022
Stock*Raw							-0.059*	0.034
Stock^2							0.042***	0.016
Constant	-0.61***	0.12	-1.80***	0.44	-1.74***	0.36	-1.22*	0.66
N	299		224		218		328	
Root Mean Square Error	0.65		0.58		0.47		0.58	
R^2		0.87		0.88	0.91			0.91
Joint test on all β_{ij}=0		0.13		0.23		0.04		0.02
Joint test on LP terms		.		.				0

Table A6: Aggregated regressions. *, ** & *** denote significance at the 10%, 5% & 1% levels; dependent variable is Value Added. Column 1 has no variables except the inputs and a constant; column 2 omits potential investment indicators; column 3 has a full set of control variables while column 4 includes IP terms.

H_{ij}=H_{ji}		1: nocon	2: pure	3: all	4: lpnocon
i	j				
Capital	Capital	-2.44	-3.2	-0.41	-1.25
	White	1.03	1.08	0.41	1
	Blue	-0.39	-1.01	-0.91	1
White	Capital	1.03	1.08	0.41	1
	White	-1.13	-0.89	-0.63	-2.54
	Blue	1.76	1.64	1.55	2.88
Blue	Capital	-0.39	-1.01	-0.91	1
	White	1.76	1.64	1.55	2.88
	Blue	-3.73	-3.53	-3.84	-2.97

Table A7: Aggregated Hicks Elasticties of Complementarity based on regressions in Table A6. Blue and white collar workers are q-complements.

ε_{ij}		1: nocon			2: pure			3: all			4: lpnocon		
i	j	Estimate	p value	η*	Estimate	p value	η*	Estimate	p value	η*	Estimate	p value	η*
Capital	Capital	-0.48	0.02	.	-0.42	0.27	.	-0.05	0.89	.	-0.56	0	.
	White	0.58	0.004	0.97	0.67	0.05	0.93	0.26	0.45	2.47	0.37	0	1
	Blue	-0.1	0.65	.	-0.25	0.48	.	-0.21	0.48	.	0.18	0	1
White	Capital	0.2	0.02	0.97	0.14	0.15	0.93	0.05	0.51	2.47	0.44	0	1
	White	-0.63	0	.	-0.55	0	.	-0.4	0	.	-0.96	0	.
	Blue	0.43	0	0.57	0.41	0.002	0.61	0.35	0.001	0.65	0.51	0.001	0.35
Blue	Capital	-0.08	0.65	.	-0.13	0.46	.	-0.12	0.46	.	0.44	0	1
	White	0.98	0.001	0.57	1.02	0.007	0.61	0.99	0.003	0.65	1.09	0.003	0.35
	Blue	-0.91	0.004	.	-0.88	0.03	.	-0.88	0.02	.	-1.53	0	.
$\boldsymbol{\varepsilon^{\rho}_{ij}}$													
Capital	Capital	-0.47	0.04		-0.38	-0.39		-0.03	0.95		-0.5	0	
	White	0.47	0.04		0.38	0.39		0.03	0.95		0.5	0	
White	Capital	0.16	0.09		0.08	0.47		0.005	0.95		0.59	0	
	White	-0.16	0.09		-0.08	-0.47		-0.005	0.95		-0.59	0	
ρ_{uj}													
Blue	Capital	-0.09	0.7		-0.15	0.52		-0.13	0.52		0.29	0	
	White	1.06	0		1.12	0		1.11	0		0.69	0	

Table A8: Aggregate elasticities of factor price with fully flexible wages and with rigid blue collar wages based on regressions in Table A6. The elasticity of factor price for blue labor with respect to white collar labor is 0.98-1.09 while the employment elasticity is 0.69-1.12.