Heterogeneous firms or heterogeneous workers? Implications for exporter premia and the gains from trade*

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Abstract

We expect trade liberalization to give rise to aggregate productivity gains, as the least efficient firms are forced out, and labor is reallocated towards the best performing firms. But the positive intra-industry reallocation effects rely on the assumption that exporters' superior performance is due to intrinsic firm efficiency. We investigate the importance of intrinsic firm efficiency relative to input quality as sources of exporters' productivity premium, employing a matched employer-employee data set for Norwegian manufacturing. Augmented measures of total factor productivity which take worker characteristics into account, indicate that $15-40$ percent of the exporter premium reflects differences in workforce rather than true efficiency. Hence, we may risk overstating the benign impact of trade on aggregate productivity if not controlling for worker heterogeneity and labor dynamics.

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1 Introduction

Internationalized firms are better performers than purely domestic firms. In trade models with heterogeneous firms trade liberalization gives aggregate productivity gains because the least productive firms are squeezed out of the market and labor is reallocated towards the best performing firms (see Melitz, 2003). But the unambiguous positive reallocation effect relies on the assumption that exporters' superior performance reflects intrinsic firm quality. But are we confusing superior firms with superior workers? If the exporter premium relates to differences in firms' workforce, rather than to intrinsic firm quality, the welfare implications of new trade theory with heterogeneous firms need to be revisited, and will obviously depend on the labor market dynamics following firm exits.

In this paper we set out to answer the question of whether exporters are intrinsically more efficient, or whether they merely employ better workers. This is required in order to obtain a more comprehensive understanding of the gains from intra-industry adjustments to trade.

We already know that exporters do better than other firms. They are larger and are more productive.[1] Differences in capital intensity explain part of the productivity differential, but the exporter productivity premium remains also after controlling for capital intensity.[2] But obtaining a better understanding of why exporters do so much better is important. It is important in order to estimate the impact of trade on reallocations and growth, and for the design of sound industrial policy. In this paper we seek to go one step further in opening the black box of the exporter premium.

Existing productivity analyses of exporters versus non-exporters are typically based on data sets which contain little information on the workforce.[3] Hence, there is little empirical evidence supporting the commonly shared view that exporters are *intrinsically* better performers than other firms. Our objective is to try to disentangle superior workers from superior firms. We do this by using a rich and comprehensive matched employer-employee data set, that allows us to calculate augmented measures of total factor productivity (TFP) that includes different measures of labor quality.

[1] See Bernard, Jensen, Redding and Schott (2007) for recent numbers and Wagner (2007) for a cross-country survey.

[2] For analysis of US exporter productivity, see e.g. Bernard and Jensen (1999), and Bernard, Jensen, Redding and Schott (2007). Analyses of other countries confirm this impression. See Wagner (2007) for a survey and Mayer and Ottaviano (2007) for evidence on European firms.

[3] There are a few studies which employ data that contain information on white and blue collar workers, see e.g. Bernard and Jensen (1999) and Pavcnik (2002).

To examine the role of labor quality versus intrinsic firm quality, we match three different Norwegian data sets: a firm panel data set with detailed firm level information covering the entire population of Norwegian manufacturing firms with information on various measures of performance and inputs; a firm panel data set with information on exports and imports (for the use as intermediates), and a worker panel data set covering the entire Norwegian labor force. The latter includes detailed information on workers' education, labor market experience, gender, and tenure and can be matched to each individual firm. The combined insight from these three data sets allows us to calculate improved measures of total factor productivity that take important worker characteristics into account, and to assess the relative importance of labor quality versus intrinsic firm efficiency as sources of exporters' productivity premia.

We calculate simple total factor productivity (TFP) measures based on the same type of input data that is most commonly used in the empirical literature on trade and heterogeneous firms, and augmented TFP measures where we adjust for differences in labor quality. By comparing the results on TFP, we find that, $15 - 40$ percent of the exporter productivity premium reflects differences in workforce rather than intrinsic firm quality.

Our empirical results establish that in order to assess the impact of increased competitive pressure on aggregate industry productivity we need information on the labor dynamics proceeding firm exit. Our findings also suggest that the aggregate productivity gains from intra-industry reallocations following trade liberalization are smaller once we account for worker heterogeneity.

The rest of the paper is organized as follows. In section 2 we review related literature. In section 3 we provide a brief overview of the data as well as characteristics of the labor force of exporters and non-exporters. Section 4 describes the two econometric routes we follow in order to account for differences in labor quality across firms. In section 5 we report interim results on different production functions, and estimate exporter premia for the simple and augmented TFP estimates, while section 6 concludes.

2 Related literature

There is now a substantial literature, based on data sets from a number of countries, documenting that exporters are more productive than other firms. Their productivity premium remains after accounting for differences in capital intensity and differences in the use of non-production versus production workers.[4] But it still remains to be explained *why* exporters do so much better than non-exporters. The hypothesis we investigate in this paper, is whether exporters appear more productive simply because they employ workers that, due to a set of different characteristics, are more productive than those working for non-exporters. To our knowledge there are no attempts to assess what, if any, part of the exporter total factor productivity premium can be attributed to superior workers rather than to the firm as such. However, there are recent studies on exporters' wage premium which are related to our work.

In their seminal paper on exporters, jobs and wages, Bernard and Jensen (1995) documented that exporters pay higher wages to production as well as to non-production workers. Proceeding their paper, there has been an increasing number of studies analyzing whether this wage premium is real, in the sense that it remains after controlling for various worker characteristics. Recent studies conclude that the wage premium still remains, see e.g. Schank, Schnabel and Wagner (2007), Munch and Skaksen (2008), and Frias, Kaplan and Verhoogen (2009).

We do not set out to explore the exporter wage premium, but our analysis is related to these studies as we also use matched employer-employee data. While the papers referred to above investigate the extent to which the wage differential between exporters and non-exporters can be explained by differences in the labor force composition, we examine the extent to which the productivity differential between the two groups can be attributed to differences in the labor force composition.

Related to our work is also the productivity analyses that have aimed to account for differences in input quality when estimating the production function. As noted already by Griliches (1957), productivity dispersion within individual industries may indeed reflect differences in the quality of inputs rather than intrinsic differences across firms. The most important reason why so many have failed to account for labor quality is probably the lack of data. One recent exception is Fox and Smeets (2008) who use a matched employer-employee data set for Danish manufacturing. They estimate a production function adding a number of worker characteristics, and assess the role of human capital variables in explaining the productivity dispersion within industries. However, their paper does not address the exporter premium, nor does it discuss the impact of heterogeneous inputs on reallocation and aggregate growth.

[4] See e.g. Bernard, Jensen, Redding and Schott (2007) for an overview of the evidence.

3 Data and descriptives

We match data on firms, trade and employees. The firm data set is Statistics Norway's Capital database, which is an unbalanced panel of all non-oil joint-stock companies spanning the years 1996 to 2005, with approximately 8,000 firms per year.[5] The panel provides information on value added, employment and capital. In 2005 the data set covered about 90 percent of manufacturing output in Norway. Value added is deflated using an industry specific commodity price index provided at the 3-digit NACE level by Statistics Norway.[6]

The Capital database is matched with data on exports and imports at the firm level assembled from customs declarations. These data make up an unbalanced panel of all yearly exports and imports values by firm. The trade data have then been merged with the capital database, based on a unique firm identifier. In line with other studies for a wide range of countries, we find that the majority of firms do not engage in exporting. In 1996 only 28.3 percent were exporting, while in 2005 this number had risen to 36.3 percent.[7]

The main source of employment and wage data for the period 1996 to 2005 is the employers register (AT) which holds annual records of worked hours and earned wages on the individual level. Statistics Norway links this register with the tax office database (LTO) to create a correspondence between the annual wage reported by the employer and those reported to the tax authorities by the individual. This joint file (ATmLTO) presents a much cleaner data set and is therefore used instead of the AT register. Besides wages by person-firm-year, the database consists of first and last dates of the employment spells within a year, total number of days worked and an indicator for full time and part time employment. The ATmLTO data are also merged with demographics data that contain information about labor market experience, years of education and gender by person-year.

Matching these three described data sets leaves us with a unique panel covering the population of all Mainland joint-stock manufacturing firms along with trade and employee data.[8]

A first, brief look at the matched employer-employee data set for Norwegian manufacturing suggests that the labor force of Norwegian exporters differs from that of non-exporters. Figure 1 provides a comparison of average tenure of the labor stock of exporters versus non-exporters

[5] Statistics Norway's capital database is described in Raknerud *et al.* (2004).

[6] http://www.ssb.no/english/subjects/08/02/20/ppi_en

[7] A firm is defined as an exporter if it sales abroad exceed 10,000 NOK.

[8] Mainland Norway consists of all domestic production activity except from the exploration of crude oil and natural gas, services activities incidental to oil and gas, transport via pipelines and ocean transport, see Statistics Norway www.ssb.no/english/subjects/09/01/terms.

across industries (see Table 6 in the Appendix for the list of industries), while Figure 2 provides the same type of comparison for labor market experience and education level[9]. Industries are indicated on the x-axis, while the y-axis shows the percentage difference between exporters and non-exporters within each sector. They illustrate that exporters typically employ workers with longer tenure, more experience and higher education than the average non-exporter. Moreover, the figures show that the labor force differences vary substantially across industries. In some industries, e.g. chemicals (nace 24) and basic metals (nace 27), the exporter premia related to tenure, experience and education are large, while in other industries, such as textiles (nace 17), there is hardly any difference between the exporters' and non-exporters' employees.

[Figure 1]

[Figure 2]

4 Production function and labor quality

In this section, we amend the standard production function procedure to account for heterogeneous workers. We discuss three alternative approaches to model and quantify labor quality, (i) Griliches' human capital approach, (ii) using the estimated wage bill as a proxy for quality, and (iii) using the average wage bill as a proxy for quality. But before describing these three approaches in more detail, we present the general production function framework.

4.1 The production function

The production function takes the form

$$y_{it} = \beta_0 + \beta_l l^*_{it} + \beta_k k_{it} + \varepsilon_{it} \tag{1}$$

where y_{it} denotes real value added of firm i in period t, l^*_{it} gives quality adjusted employment, and k denotes the real value of capital services (all in logs).[10] β_l and β_k are the input elasticities of labor and capital. ε_{it} is the residual and is defined by $\varepsilon_{it} \equiv \mu_{it} + \eta_{it}$, where μ_{it} is unobserved

[9] Tenure is measured as number of years worked for the firm where the person is currently employed. Education level is measured in terms of number of years of education. Labor market experience is measured as total number of years worked. Labor characteristics are averaged at the industry level by using firm employment as weights.

[10] We describe the deflators used and the construction of the capital measure in the appendix.

productivity and η_{it} is noise (either measurement error or a shock to productivity which is not forecastable during the period in which labor can be adjusted).

There is a set of estimation issues that have to be dealt with.

- If μ_{it} is observed by the firm before it chooses the optimal amount of labor and capital, so that the firm adjusts its labor input and k_{it} in response to μ_{it}, the estimated coefficients will be biased. Introducing labor quality into the production function exacerbates this problem. Productivity and labor quality may be complements, so higher μ_{it} can lead to both higher l^*_{it} (e.g. through skill upgrading) and y_{it}.

- Selection bias: Unobserved productivity may be correlated with a firm's exit decision.[11]

- There may be measurement error in y_{it} because the industry-level deflators only partially capture firm-level price movements. This implies that the resulting productivity estimates capture price and demand shocks. A number of studies, e.g. Klette and Griliches (1996), Klette (1999) and De Loecker (2007), propose methods to correct for this potential bias. Since the main focus in this paper is on input heterogeneity, we do not deal with these issues here.

We correct for (1) and (2) by using a modified version of the Olley-Pakes (1996) technique, which is adjusted to account for labor quality heterogeneity, and follow a three-step procedure. First, consider a dynamic model of investment with heterogeneous firms resulting in an equilibrium policy function $i_{it} = f(\mu_{it}, k_{it})$. Provided that f is strictly increasing in μ_{it}, $\mu_{it} = f_t^{-1}(i_{it}, k_{it})$. The production function can then be written

$$y_{it} = \beta_l l^*_{it} + \phi_t\left(k_{it}, i_{it}\right) + \eta_{it} \tag{2}$$

where $\phi_t\left(k_{it}, i_{it}\right) = \beta_0 + \beta_k k_{it} + f_t^{-1}(i_{it}, k_{it})$. We estimate (2) by OLS or Non-Linear Least Squares (NLS) depending on the method by which we account for labor quality differences. We approximate ϕ_{it} by a $4th$ order polynomial expansion with a full set of interactions. We allow the polynomial to vary over time by including year dummies as well as year dummies interacted with investment and capital.

Second, we find survival probabilities P_{it} by estimating a probit model of exit. Again, the

[11] For example, a firm's productivity and capital stock may jointly increase the probability of survival. Then, ω_{it} and k_{it} are negatively correlated in the selected sample. This creates a downward bias in the estimate of β_k.

regressors are a $4th$ order polynomial expansion along with year dummies.

$$P_{it} = \Pr\left[\chi_{it+1} = 1\right] = h_t\left(i_{it}, k_{it}\right), \tag{3}$$

where $\chi_t = 1$ if the firm is present in year t. Third, we use the estimates of β_l, $\phi_t\left(k_{it}, i_{it}\right)$ and P_{it} and substitute them into

$$y_{it+1} - \beta_l l^*_{it+1} = \beta_k k_{t+1} + g\left(P_{it}, \phi_t - \beta_k k_t\right) + \xi_{it+1} + \eta_{it+1} \tag{4}$$

where $g()$ approximates $E\left[\mu_{it+1}|\mu_{it}, \chi_{it+1} = 1\right]$, that is, the firm's expectation of the productivity realization (which will influence investment and capital stock). ξ_{it+1} is unanticipated firm TFP. We estimate (4) by Non-Linear Least Squares (NLS) and obtain an unbiased estimate of β_k.

4.2 Griliches' measure of human capital

To account for differences in firms' labor stock we follow Griliches (1957), who argued that mismeasured labor quality is a major explanation for productivity dispersion. Griliches' approach has more recently been employed by e.g. Fox and Smeets (2008), Hellerstein and Neumark (2006) and Van Biesebroeck (2007).

For each firm in our data set, we have demographic information on the entire workforce. We assume that workers with different demographic characteristics are perfectly substitutable inputs with potentially different marginal products. The sensitivity of this approach is discussed below.[12] For example, assume that workers are distinguished only by education, high school or college. Then effective labor input is $L^*_{it} = z_H H_{it} + z_C C_{it}$, where C_{it} is the number of college graduates, H_{it} the number of high school graduates and z_m is the marginal productivity of each type $m = H, C$. L^* can be re-written as

$$L^*_{it} = z_H L_{it}\left[1 + \left(\theta_C - 1\right) x_{Cit}\right] \tag{5}$$

where $\theta_C \equiv z_C/z_H$ depicts the marginal productivity of college relative to high school graduates, $x_{Cit} \equiv C_{it}/\left(C_{it} + H_{it}\right)$ is the number of college graduates relative to the total workforce. Taking

[12] Rosen (1983) describes issues related to this specification of labor input.

logs and substituting (5) into the production function (2) yields

$$y_{it} = \beta_l \left(l_{it} + q_{it}\right) + \phi_t \left(k_{it}, i_{it}\right) + \eta_{it} \tag{6}$$

where $q_{it} \equiv \ln Q_{it} = \ln\left[1 + \left(\theta_C - 1\right) x_{Cit}\right]$ denotes the quality adjustment. The relative marginal productivity θ_C can then be estimated, using data on output, capital, number of workers and the education composition of the workforce.

In practice, we are not only distinguishing workers by high school or college degree, but by a range of various characteristics. Including a vector of characteristics expands the dimensionality of the problem since in principle every combination of relative productivities determines L^*. To reduce the dimensionality, we follow Hellerstein et al (1999) and impose two restrictions on the problem. First, we restrict the relative marginal products of two types of workers within one demographic group to be equal to the relative marginal products of those same two types of workers within another demographic group.[13] Second, we restrict the proportion of workers in an establishment defined by a demographic group to be constant across all other groups.[14]

The worker characteristics available to us are: Gender, years of labor market experience, years of education and tenure (years of experience in current firm). To allow for possible non-linear effects, labor market experience, education and tenure is constructed as the number of workers in group k relative to total firm workforce. Workers are split into five groups according to labor market experience: (X_1) <13 years, (X_2) 13-19 years, (X_3) 20-25 years, (X_4) 26-32 years and (X_5) more than 33 years; while the education groups are (E_1) <11 years, (E_2) 11-12 years, (E_3) 13-14 years, (E_4) 15-16 years, and (E_5) more than 17 years; and the tenure groups are (T_1) <1 year, (T_2) 1-2 years, (T_3) 2-7 years, (T_4) more than 7 years.[15]

With these assumptions, the quality index becomes:

$$\begin{aligned} Q_{it} = {} & \left[1 + \left(\theta_M - 1\right) x_{Mit}\right]\left[1 + \left(\theta_S - 1\right) x_{\mathrm{Si}\,t}\right] \\ & \left[1 + \left(\theta_{E_2} - 1\right) x_{E_2it} + .. + \left(\theta_{E_5} - 1\right) x_{E_5it}\right] \\ & \left[1 + \left(\theta_{X_2} - 1\right) x_{X_2it} + .. + \left(\theta_{X_5} - 1\right) x_{X_5it}\right] \\ & \left[1 + \left(\theta_{T_2} - 1\right) x_{T_2it} + .. + \left(\theta_{T4} - 1\right) x_{T_4it}\right] \end{aligned} \tag{7}$$

[13] E.g. the relative productivity of male relative to female workers is identical irrespective of experience, education, etc.

[14] E.g. males are equally represented in all education levels, tenure groups and so forth.

[15] The groups are constructed so as to allow for as much variation in the data set as possible. This is achieved by splitting the workforce into groups according to years of labor market experience, tenure and education in a way so that each group consists of approximately the same number of employees.

where M denotes share of males in the labor force, while E, X and T denote the education, experience and tenure groups (e.g. x_{E_2it} denotes the share of of workers with 11-12 years education in firm i at time t). Note that E_1, X_1 and T_1 are the omitted categories, implying that the productivities θ_{E_k}, θ_{X_k} and θ_{T_k} are measured relative to the omitted groups. For example, θ_{E_2} measures the marginal productivity of workers with 11-12 years education relative to workers with < 11 years of education. Similarly, θ_M measures the marginal productivity of male relative to female workers.

The model is more flexible than a Cobb-Douglas with as many inputs as worker characteristics because the production function is defined even if $x_{mit} = 0$ (which appears in the data). This means that it is also especially suitable for our analysis, as we want to be able to compare TFP values for estimation with and without labor quality adjustment.

Estimation of equation (6) is carried out with non-linear least squares since the terms in Q_{it} enter non-linearly. Also note that we retrieve estimates of $\theta_{\widehat{m - 1}}$, so relative marginal productivities are $\widehat{\theta}_m = \theta_{\widehat{m - 1}} + 1$. After estimation of equation (6), the second and third stages of the Olley-Pakes (1996) technique are performed, so that all the coefficients of the production function are recovered.

One concern of the Griliches approach is our reliance on the assumption that workers with different demographic characteristics are perfectly substitutable inputs. Although restrictive, this assumption enables us to formulate a tractable estimating equation and to obtain an index of quality. In the Appendix we explore an alternative strategy where we assume a Cobb-Douglas structure which allows for imperfect substitution between labor types. We report results both for the baseline as well as the modified approach to Griliches' Human capital.

The workforce characteristics in the data set cover important aspects of worker efficiency but is by no means exhaustive. Since there may be correlation between omitted and observable characteristics the estimated coefficients may be biased. In the sections below we describe two alternative methods of backing out worker quality, where we account for both observed and unobserved skills.

4.3 The wage bill as a proxy for labor quality

Our second approach is to adjust for labor quality by using the wage bill as a measure of the quality of the workforce. The underlying assumption is that wages reflect marginal products in a competitive labor market. Even if the labor market is not perfectly competitive, we would reckon that wages are likely to be highly correlated with workers' efficiency.[16] As argued by a.o. Fox and Smeets (2008), using the wage bill instead of the number of workers makes the methods of measuring physical capital and human capital more symmetric: Physical capital is measured in terms of monetary units to reflect the quality of the machinery employed, while using the wage bill to proxy for labor input also implies measuring labor in terms of its expense in order to reflect its quality.

We let the quality adjusted employment be modelled as

$$l^*_{it} = \ln w_{it} + \ln L_{it}, \tag{8}$$

where L_{it} still denotes the number of workers and w_{it} is the average wage earned in firm i at time t, and substitute this into the production function described above: $y_{it} = \beta_0 + \beta_l l^*_{it} + \beta_k k_{it} + \varepsilon_{it}$.

4.4 The estimated wage bill as a proxy for labor quality

Our third approach is to estimate labor quality by using information about wages from every employer-employee spell. As argued above, even if the labor market is not perfectly competitive, we would reckon that wages are likely to be highly correlated with workers' efficiency. However, the empirical evidence on the importance of person as well as firm characteristics for wage determination (see Abowd et al, 1999) suggests that using firm average wages to proxy for labor quality delivers an inaccurate measure of workforce quality. It may also lead to a systematic downward bias of the total factor productivity of exporters.[17] Therefore we proceed by first estimating a wage regression including person as well as firm effects, and second calculating predicted wages that reflect worker characteristics but not firm effects. That is, the wage that workers would have been paid if they were hired by an average firm. Third, the predicted wage, averaged over all employees within a firm, is used as a proxy for workforce quality when we estimate the production function.

We follow Abowd et al (1999) and consider the wage regression

$$\ln w_{jt} = \varphi_j + \Psi_{I(j,t)} + x_{jt}\lambda + \varepsilon_{jt} \tag{9}$$

[16] Shaw and Lazear (2007) find that the very steep learning curve in the first eight months on the job is not reflected in equal percentage pay gains. However, the pattern of productivity rising more rapidly than pay reverses after two years of tenure.

[17] In the presence of rent-sharing, the wage bill will overstate effective labor input. Also, there is empirical evidence documenting that exporters pay higher wages and that the wage premium remains after controlling for workforce characteristics. Both mechanisms will lead to a downward bias in estimated TFP.

where w_{jt} is the nominal wage for person j at time t per unit of time (year), measured in logs and relative to its' grand mean, θ_j is a person fixed effect, $\Psi_{I(j,t)}$ is a fixed effect for the firm at which worker j is employed at date t (denoted $I(j,t)$), x_{jt} is a vector of P time-varying exogenous characteristics of individual j, measured relative to their grand means, and ε_{jt} is the statistical residual.

Identification of $\Psi_{I(j,t)}$ relies on workers switching between firms and that firms are part of a connected mobility group of establishments; for details see Abowd, Creecy and Kramarz (2002). This requires turnover. By calculating mean tenure for each of the ten years, we find that average tenure varies between 5.8 and 6.5 years. The fixed effects are estimated under the identifying restrictions that $\sum_j \varphi_j = 0$ and that the last firm effect is zero, within each mobility group.

Estimating the model by OLS requires that the error term is uncorrelated with the covariates, formally, $E[\varepsilon_{jt}|j,t,I(j,t),x_{jt}] = 0$. Movements in ε_{jt} (for example due to time-varying worker productivity) must therefore be uncorrelated with firm effects. This assumption is often referred to as exogenous mobility in the employer-employee literature. Mobility should therefore not be driven by time-varying unobservables.

We estimate the model on the whole population of Norwegian firms and all full-time employees in the years 1996 to 2005.[18] The time-varying observables included in the x_{jt} vector are: firm tenure (full-time equivalent years of work in the current workplace), firm tenure squared, years of labor market experience, this variable raised to the power of two, three and four, and year dummies. The data are described in more detail the data section as well as in the appendix.

The normal equations for least squares estimation of both fixed person and firm effects are of very high dimension and it is not possible to estimate the model by standard methods when the number of firms and persons is high. But as shown in Abowd et al (2002), exact least squares solutions are available by using an iterative conjugate gradient method.

After estimating equation (9), we calculate $\ln \widehat{w}_{jt} = \widehat{\varphi}_j + x_{jt}\widehat{\lambda}$. The estimated person effects $\widehat{\varphi}_j$ are estimates of the value of all time-invariant individual characteristics, including both unobserved and observed skill. $x_{jt}\widehat{\lambda}$ is the value of time-variant worker characteristics, so their sum is an estimate of the overall value of skills of individual j at time t. The remaining term $\Psi_{I(j,t)}$ is the firm-specific wage premium.

[18] Limiting the analysis to manufacturing firms would reduce the number of observations needed to identify worker fixed effects.

We take the weighted average of this measure for each firm i in every period t:

$$\ln \widehat{w}_{it} = \sum_{j:I(j,t)=i} \omega_{jt} \ln \widehat{w}_{jt} \tag{10}$$

where ω_{jt} are weights that reflect the individual's work effort in a given year (the construction of weights as well as other details are delegated to the Appendix). We use this measure as an estimate of the average skill of the workforce for every firm-year. Our measure of the effective labor force l_{it}^* is then $l_{it}^* = \ln \widehat{w}_{it} + \ln L_{it}$, which we substitute into the production function, $y_{it} = \beta_l l_{it}^* + \phi_t (k_{it}, i_{it}) + \eta_{it}$, which in turn is estimated. Eventually, the second and third stages of the Olley-Pakes (1996) technique are performed, so that all the coefficients of the production function are recovered.

5 Results

We estimate the standard and the augmented production function, and compare the estimates. We demonstrate the importance of correcting for labor quality. In addition, we use our estimates to compute standard and adjusted firm productivity and calculate a standard and adjusted export TFP premium. Finally, we show that the exporter TFP premium is significantly reduced after controlling for worker heterogeneity, which suggest that exporter superiority is not only related to intrinsic firm efficiency but also to so superior workers.

5.1 Production and quality

Table 1 reports production function estimates for the model without quality adjustment (column 1), as well as for the models with quality adjustments using the Griliches approach (column 2), the estimated wage approach (column 3), and the average wage approach (column 4). With the Griliches' approach, the coefficients associated with the labor quality characteristics enter nonlinearly, and therefore requires the use of NLS in the first stage of the Olley-Pakes procedure. The other approaches are based on OLS in the first stage. To simplify the presentation, the results in Table 1 are based on the pooled sample of all manufacturing firms. Sector-specific estimates of the production function, which form the basis for the subsequent TFP analysis, are presented in the Appendix (Table 7).

[Table 1]

The coefficients for employment and capital are significant and positive in all cases. In column (2), we find that there is a significant positive monotonic relationship between education and marginal productivity. Specifically, the education coefficients rise from 0.1 to 1.2, implying that the marginal productivity of workers with 11 or more years of education is between 10 and 120 percent higher than the group of workers with education less than 11 years. With respect to labor market experience our results suggest a non-monotonic – bell-shaped – relationship. A bit surprisingly, firm tenure does not affect relative productivities.

We also estimate the first stage of the production function with quality adjustments for non-exporters and exporters separately, see Table 2.[19] A Wald test confirms that the coefficients for Male, Tenure 2-7 years, Education 13-14 years, and Education 15-16 years are significantly higher for exporters than for non-exporters. This suggests that e.g. the return to education is higher among exporters than non-exporters. This provides one explanation for why exporters on average employ more workers with higher education (see Figure 2).

[Table 2]

Table 3 reports interim results from the two-way fixed effects wage model. Again, firm tenure has little explanatory power, while experience is clearly important for wage determination. Plotting the experience polynomial using the estimated coefficients reveals that the wage schedule is bell-shaped, mirroring the results from the Griliches approach.

[Table 3]

Finally we compare the quality indices produced by the two methods. A simple indicator is the correlation between Q_{it}, evaluated using the estimated values of θ_m, and $\ln \widehat{w}_{it}$. Using all firms in the sample and calculating correlations by sector, we find that the correlation, averaged over all sectors, is 0.19.[20] Truncating the sample by dropping firms with less than 20 employees eliminates a fair amount of noise and increases the correlation to 0.37.[21] The fact that the correlation is less than one, presumably reflects that, even after controlling for firm effects, wages only imperfectly reflect marginal productivities in the Norwegian labor market.

[19] Exporters (non-exporters) are here defined as the set of continuous exporters (non-exporters), i.e. firms switching export status are excluded from the sample.

[20] The corresponding correlation between Q_{it} and actual wages ($\ln w_{it}$) is 0.26. The correlation between $\ln \widehat{w}_{it}$ and $\ln w_{it}$ is 0.45.

[21] The corresponding correlation between Q_{it} and actual wages ($\ln w_{it}$) is 0.42. The correlation between $\ln \widehat{w}_{it}$ and $\ln w_{it}$ is 0.72.

5.2 Exporter premia

Our next step is to use the sector-specific estimate of the production function to calculate total factor productivity residuals. Total factor productivity is calculated as

$$tfp_{it}^{v} = y_{it} - \widehat{\beta}_{l}^{v} l_{it}^{*v} - \widehat{\beta}_{k}^{v} k_{it} \tag{11}$$

where superscript v denotes the chosen production function specification, subscript i still denotes the firm, and t the year. TFPs are calculated using no quality adjustment, the Griliches approach, the estimated wage approach, and finally using average wages.

Subsequently, we follow Bernard and Jensen (1999) and calculate exporter premia for TFP as well as other firm variables, controlling for differences in size as well as industry:

$$z_{it} = \beta_k + \alpha_t + \psi_{kt} + \rho Ex_{it} + \gamma L_{it} + \varepsilon_{it} \tag{12}$$

where z_{it} is tfp_{it}^{q} as well as other firm characteristics, Ex_{it} is an exporter dummy, and β_k, α_t and ψ_{kt} denote industry fixed effects, year dummies and industry-year interactions, respectively. Hence, $\exp(\rho)$ measures the exporter premium in percent within the same industry-year and for same firm size. The premia we consider are labor productivity, TFP (unadjusted and quality adjusted), capital stock (total and split into structures and machinery), profits, average tenure, education level, labor market experience, wages (actual and predicted) as well as the quality index Q_{it}.

Productivity: In line with previous studies we find that exporters are more productive. The unadjusted TFP premium is rather similar to what is found in the U.S. (13.5 percent in 1992 in Bernard and Jensen, 1999). Once we adjust for differences in labor quality, using the Griliches approach, the average wage bill or the estimated wage bill (Mincer), the exporter premium is reduced. Hence, the exporter premium does not only reflect intrinsic firm differences, but also differences in the labor force.

Based on the pooled sample (across years and industries) the mean reduction in the exporter premium is 15 percent in the Griliches case, and $30-40$ percent when we adjust for labor quality using average or predicted wages. Based on a simple Wald test, we reject the hypothesis that the adjusted premia are identical to the unadjusted one, at the 0.01 significance level. To check the robustness of our results, we re-estimated TFP using the alternative model of Griliches' human capital with imperfect substitution between labor types,[22] and calculated the associated exporter premium. This gives a TFP premium of 5.0 percent, roughly 40 percent lower than the unadjusted TFP premium. We conclude that our exporter premium results are robust to alternative assumptions about labor substitutability.

Skills and wages: Table 4 summarizes the different exporter premia. In line with previous studies we find that exporters have higher profits, are more capital intensive and pay higher wages. But our matched employee-employer data set also reveals that exporters have a labor force that differs from other firms. Their workers are more experienced, have higher education and longer tenure. The difference in workforce skills between exporters and non-exporters is also reflected by Griliches measure of human capital (Q_{it}) and the quality measure developed on the basis of the Mincer regression ($\ln \widehat{w}_{it}$). 48 percent of the wage premium paid by exporters can be ascribed to worker rather than firm characteristics. We arrive at this result by dividing the exporter premium for the quality measure $\ln \widehat{w}_{it}$ (which represents predicted wages based on worker characteristics only) with the premium for actual wages.

Complementarities: Finally, it is also interesting to note that the difference between exporters and non-exporters is more substantial with respect to machinery than with respect to structures. This suggests that exporters are both more skill intensive and have a higher degree of automation.

[Table 4]

Sectoral differences: We proceed by splitting the results on exporter productivity premium by sector. Table 5 shows that in 15 out of 18 industries the exporter TFP premium is reduced if we adjust for differences in the labor stock using the Mincer adjustment (11 out of 18 in the Griliches case). Among the industries where the premium is reduced, the reduction is between 3 and 64 percent in the Mincer case. The results differ somewhat depending on whether TFP is adjusted using the average wage, the estimated wage (Mincer) or the Griliches approach. But we observe that in most of the industries experiencing a significant reduction in the exporter TFP premium when we adjust for quality, the reduction is supported by all three approaches. The industries where labor composition appears to impact substantially on measured productivity are Electrical machinery (nace 31), Instruments (nace 33) and Other transport equipment (nace 35)[23]. These industries have in common that they are among the most skill intensive industries

[22] The model is presented in detail in the appendix. Results are available upon request.
[23] Other transport equipment primarily refers to shipbuilding.

in Norwegian manufacturing. Once we account for differences in the labor force within these industries the exporter TFP premium falls by roughly 40 percent (averaged across the three industries, using both Griliches and Mincer adjustment).

[Table 5]

6 Conclusions

Previous research has shown that internationalized firms are better performers than purely domestic firms. Hence, in trade models with heterogeneous firms trade liberalization gives aggregate productivity gains because labor is reallocated towards the best performing firms. But the unambiguous positive reallocation effect relies on the assumption that exporters' superior performance is only due to intrinsic firm quality.

In order to assess the relative importance of input quality versus intrinsic firm quality as sources of exporters' productivity premium, we use a unique data set of firms, worker characteristics and trade. This allows us to calculate improved measures of total factor productivity which controls for the presence of worker heterogeneity.

The data reveal that dispersion in average worker characteristics across firms is large. Employees in exporting firms have higher earnings, they are more tenured, educated and experienced – controlling for firm size and sector. Exporters are at the same time more productive, consistent with models of firm heterogeneity and input quality such as Verhoogen (2008). Furthermore, on average, the exporter TFP premium falls by between $15 - 40$ percent after controlling for workforce characteristics, depending on the method used. This tells us that the gains from trade due to the exit of the less productive firms may be overstated if the heterogeneity in inputs is not properly accounted for. Hence, in order to assess the impact of fiercer international competition and firm exit on aggregate productivity, further research is needed to help us understand properly the labor market dynamics and reallocations of resources following firm exits.

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A Appendix

A.1 Constructing the labor stock variable

To construct the workforce variable (L_{it}) we use detailed information on start and end dates of the employer-employee relationship as well as on working hours. The data set provides details about (1) the start and end dates of the employer-employee relationship and (2) whether hours worked per week is (a) Less than 10 hours, (b) 10-30 hours or (c) more than 30 hours per week. Ideally we would to know the exact number of hours worked by each employee. Since this information is not available, we restrict the sample to the employees who worked more than 30 hours a week in order to obtain a measure of the work force that is as accurate as possible. Each employee is then ascribed a weight of 1 if he (she) worked the entire year, while we adjust the weight downwards if the employee did not work through the whole year (started after 1 January or ended before 31 December).

A.2 Constructing the wage variable

The employer-employee data set records every worker-employee relationship of any length. w_{jt} is constructed by taking actual wage payments and rescaling the amount to yearly wages, if the duration is less than one year. In some cases a person has many employers during one year. In those cases we only use the employer-employee relationship with the longest duration. Since exact hours worked is not known, we estimate equation (9) on the population of full-time workers exclusively (i.e. the employees with more than 30 hours per week). Average predicted wage (q_{it}) of firm i is therefore based on the predicted wage of full-time workers only. This is unlikely to bias q_{jt} much as long as the skill level – and thus predicted wage – of part-time workers is correlated with average skills of the remaining workforce and as long as the part-time share of workers is low. In 2004, only 10.9 percent of employer-employee relationships in manufacturing were part-time.

A.3 Other variables

Value added and value of capital services are deflated using industry specific (3 digit NACE) deflators. The value of capital services is measured as annualized user cost of capital (including leased capital) relative to hours worked, and is calculated as $k_{it} = \sum_h k_{it}^h = \log((r + \delta_h)K_{it}^h)$; where K_{it}^h is the real net capital stock of type h, for firm i at time t. h is either buildings and land (b) or other tangible fixed assets (o),[24] while r is the real rate of return, which is based on the average real return on 10-year government bonds in the period 1996-2004 (4.2 percent), and δ_h is the median depreciation rates obtained from accounting statistics.

A.4 Alternative production functions

In the main text, we assume that different types of labor are perfect substitutes. Although restrictive, this assumption enables us to formulate a tractable estimating equation and to obtain an index of quality. In this section, we explore an alternative strategy that allows for imperfect substitution between labor types. Specifically, we assume a Cobb-Douglas structure, so

$$l_{it}^{*} = \sum_{m \in \Omega} z_m l_{mit} \tag{13}$$

where l_m is a labor of type m (in logs), M is the set of different types (e.g. high school and college types), z_m is the output elasticity of type m.

For expositional purposes, assume two binary types, college/high school (C/H) and male/female (M/F). In that case, $\Omega = \{MH, MC, FH, FC\}$. Also assume, as in the main text, that subgroups are equally well represented in each main group, i.e. $x_M = L_{MC}/\left(L_{MC} + L_{FC}\right) = L_{MH}/\left(L_{MH} + L_{FH}\right)$. Then equation (13) can be rewritten as

$$\begin{aligned}
l_{it}^{*} &= \sum_{m \in M,F} \sum_{n \in C,H} z_{mn} l_{mnit} \\
&= \sum_{m \in M,F} \sum_{n \in C,H} z_{mn} \left(l_{mit} + l_{nit} - l_{it}\right) \\
&= \sum_{m \in M,F} l_{mit} \sum_{n \in C,H} z_{mn} + \sum_{n \in C,H} l_{nit} \sum_{m \in M,F} z_{mn} - l_{it} \sum_{m \in M,F} \sum_{n \in C,H} z_{mn} \\
&= \alpha_1 l_{Mit} + \alpha_2 l_{Fit} + \alpha_3 l_{Cit} + \alpha_4 l_{Hit} - \left(\alpha_1 + \alpha_2\right) l_{it} \\
&= \alpha_1 \ln x_{Mit} + \alpha_2 \ln x_{Fit} + \alpha_3 l_{Cit} + \alpha_4 l_{Hit}
\end{aligned}$$

where we used the assumption that $L_{mnit} = L_{nit} x_{mit} = L_{mit} L_{nit}/L_{it}$ from the first to the second line. The estimating coefficients α represent the sum of output elasticities over each subgroup, e.g. α for female (α_2) is the sum of z_{FC} and z_{FH}.

Using the same set of labor characteristics as in the main text,

$$\Omega = \left\{S = \left(M,F\right), E = \left(E1,..,E5\right), X = \left(X1,..,X5\right), T = \left(T1,..T4\right)\right\}$$

[24] The latter group consists of machinery, equipment, vehicles, movables, furniture, tools, etc.

l^* becomes

$$l_{it}^* = \alpha_1 \ln x_{Mit} + \alpha_2 \ln x_{Fit} + \sum_{m \in \Omega_{-S}} \alpha_m l_{mit} \tag{14}$$

where Ω_{-S} denote that we sum over all elements in Ω except M, F.

Finally, we have to make sure that every $0 < x_{mit} < 1$, since x_{mit} taking the value 0 or 1 is not consistent with the Cobb-Douglas framework. We solve this by adding/subtracting a small ε to any $x_{mit} = 0$ or $x_{mit} = 1$.

We proceed as in the main text by estimating the production function (2) together with (14), using the Olley-Pakes procedure, by sector. Next we calculate adjusted TFP indices and construct the adjusted TFP premium, using (12), results are reported in Tables 4 and **??**.

A.5 Figures and Tables

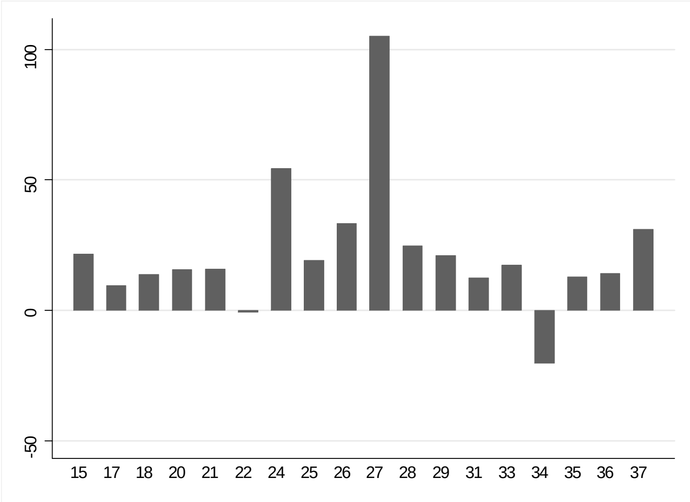

Figure 1: Job tenure. Difference between exporters and non-exporters in %, by industry.

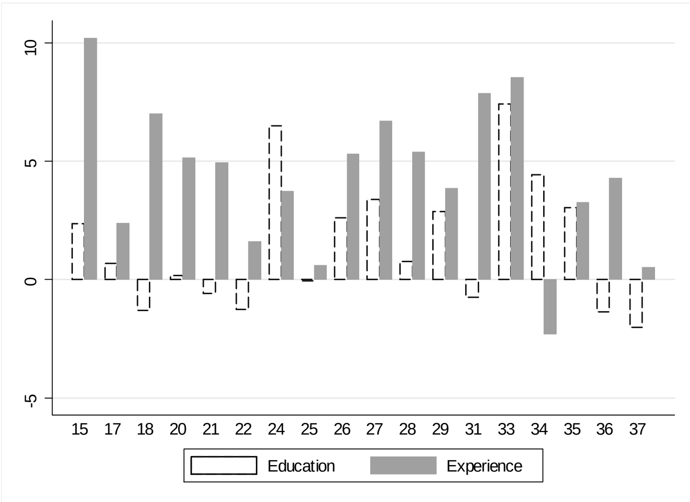

Figure 2: Labor market experience and education. Difference between exporters and non-exporters in %, by industry.

Table 1: Olley-Pakes production function estimates

	(1) Without Labor quality (LQ)		(2) With LQ Griliches HC		(4) With LQ Estimated wage		(4) With LQ Average wage	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Employment($\widehat{\beta_l}$)	.687^a	(.003)	.690^a	(.003)	.658^a	(.003)	.680^a	(.002)
Capitalservices($\widehat{\beta_k}$)	.205^a	(.004)	.214^a	(.004)	.215^a	(.004)	.193^a	(.003)
Maleshare			.048^a	(.014)				
Tenure1-2			-.062^c	(.036)				
Tenure2-7			.023	(.037)				
Tenure7+			.040	(.037)				
Education11-12			.103^a	(.021)				
Education13-14			.268^a	(.021)				
Education15-16			.993^a	(.054)				
Education17+			1.208^a	(.061)				
Experience 13-19			.199^a	(.028)				
Experience 20-25			.230^a	(.028)				
Experience 26-32			.267^a	(.028)				
Experience 33+			.204^a	(.028)				
R-squared	.91		.91		0.91		.93	
Number of obs.	43535		43535		43535		43535	

Note: All sectors pooled. In (2), female, tenure 0-1, education 0-11, and experience 0-13 are the omitted categories. ^{a}significant at 1% level, ^{b}significant at 5% level, ^{c}significant at 10% level.

Table 2: Olley-Pakes 1. stage production function estimates with Griliches Human Capital: Non-exporters versus Exporters exporters

Griliches HC	Non-Exporters		Exporters	
	Coef.	S.E.	Coef.	S.E.
Employment($\widehat{\beta}_l$)	.677[a]	(.006)	.683[a]	(.011)
Capitalservices($\widehat{\beta}_k$)				
Maleshare	-.027	(.020)	.143[a]	(.047)
Tenure1-2	-.063	(.041)	.094	(.147)
Tenure2-7	.091[b]	(.045)	.398[b]	(.175)
Tenure7+	.121[a]	(.046)	.387[b]	(.172)
Education11-12	.153[a]	(.029)	.113	(.076)
Education13-14	.287[a]	(.030)	.453[a]	(.078)
Education15-16	.772[a]	(.078)	1.583[a]	(.231)
Education17+	.896[a]	(.104)	1.023[a]	(.214)
Experience 13-19	.155[a]	(.040)	.316[a]	(.122)
Experience 20-25	.216[a]	(.040)	.331[a]	(.138)
Experience 26-32	.253[a]	(.039)	.396[a]	(.105)
Experience 33+	.218[a]	(.042)	.237[b]	(.114)
R-squared	.82		0.90	
Number of obs.	24381		11414	

Note: All sectors pooled. Female, tenure 0-1, education 0-11, and experience 0-13 are the omitted categories. Exporters (non-exporters) are defined as the set of continuous exporters (non-exporters).
[a]significant at 1% level, [b]significant at 5% level, [c]significant at 10% level.

Table 3: Wage regression with person and firm effects (1996-2005)

	Coef.
Tenure	-.003
Tenure^2/100	.007
Experience	.079
Experience^2/100	-.683
Experience^3/1,000	.174
Experience^4/10,000	-.018
Year dummies	Yes
R^2	.68
N	15.7 mill
std(θ_i)	.62
std$\left(\Psi_{J(i,t)}\right)$	.25
corr$\left(\Psi_{J(i,t)}, \theta_i\right)$	.03

Table 4: Exporter premia

	Exporter premia
Labor productivity	15.6^a
TFP unadjusted	8.1^a
TFP adjusted; Griliches HC	6.9^a
TFP adjusted; Griliches HC, with C-D	5.0^a
TFP adjusted; Estimated wage (Mincer)	5.6^a
TFP adjusted; Average wage	5.1^a
Capital stock per worker	35.8^a
Structures per worker	17.7^a
Machinery per worker	35.8^a
Profit margin	41.9^a
Tenure	5.2^a
Wage	5.4^a
Years of education	0.8^a
Labor market experience	3.9^a
Quality index 1 (Q_{it})	1.0^a
Quality index 2 ($\ln\widehat{w}_{it}$)	2.6^a
Industry dummies (nace 2)	Yes
Year dummies	Yes
Industry-year interactions	Yes
N	74099

Note: TFP is calculated by using Olley-Pakes and industry specific coefficients.
Estimates are based on the panel 1996-2005.
^{a}significant at 1% level, ^{b}significant at 5% level, ^{c}significant at 10% level.
A firm is defined as an exporter if the export value exceeds 10.000 NOK in a given year.

Table 5: Exporter TFP premia by sector

Industry	TFP Unadjusted	TFP Griliches	TFP Average wage	TFP Mincer
Food products and beverages	12.0^{a}	10.8^{a}	6.7^{a}	9.1^{a}
Textile products	6.2^{a}	7.9^{a}	6.6^{a}	3.9^{a}
Wearing apparel., fur	13.0^{a}	10.7^{a}	6.7^{a}	12.3^{a}
Wood and wood products	8.0^{a}	8.2^{a}	5.1^{a}	5.8^{a}
Pulp, paper and paper products	-3.8	-4.6	2.3	0.3
Publishing, printing, reproduction	3.7^{a}	4.9^{a}	3.2^{a}	2.3^{a}
Chemicals and chemical products	-5.7	-4.6	-4.7	-.7
Rubber and plastic products	7.0^{a}	6.4^{a}	5.9^{a}	6.1^{a}
Other non-metallic mineral products	3.5^{b}	4.3^{b}	2.5^{b}	3.4^{b}
Basic metals	12.9^{a}	6.6^{b}	9.4^{a}	11.0^{a}
Fabricated metal products	1.0	0.7	-0.4	-1.3
Machinery and equipment n.e.c.	11.9^{a}	9.5^{a}	7.1^{a}	8.7^{a}
31Electrical machinery and apparatus	12.2^{a}	9.0^{a}	6.1^{a}	8.1^{a}
33Instruments, watches and clocks	12.5^{a}	3.7^{c}	-3.4	4.5^{b}
Motor vehicles, trailers, semi-tr.	6.7^{b}	5.6^{b}	8.5^{b}	8.0^{b}
35Other transport equipment	11.4^{a}	10.3^{a}	5.5^{a}	8.5^{a}
Furniture, manufacturing n.e.c.	12.9^{a}	11.7^{a}	9.6^{a}	9.4^{a}
Recycling	17.1^{a}	17.5^{a}	15.4^{a}	10.5^{b}

Note: Estimates are based on the panel 1996-2005.

^{a}significant at 1% level, ^{b}significant at 5% level, ^{c}significant at 10% level.

A firm is defined as an exporter if the export value exceeds 10.000 NOK in a given year.

Table 6: Industries

Nace	Industry
15	Food products and beverages
16	Tobacco products
17	Textile products
18	Wearing apparel., fur
19	Footwear and leather products
20	Wood and wood products
21	Pulp, paper and paper products
22	Publishing, printing, reproduction
23	Refined petroleum products
24	Chemicals and chemical products
25	Rubber and plastic products
26	Other non-metallic mineral products
27	Basic metals
28	Fabricated metal products
29	Machinery and equipment n.e.c.
30	Office machinery and computers
31	Electrical machinery and apparatus
32	Radio, TV sets, communication equipment
33	Instruments, watches and clocks
34	Motor vehicles, trailers, semi-tr.
35	Other transport equipment
36	Furniture, manufacturing n.e.c.
37	Recycling

Table 7: Olley-Pakes production function estimates by sector

Nace	15	17	18	20	21	22	24	25	26	27	28	29	31	33	34	35	36	37
Without labor quality adjustments																		
$\widehat{\beta}_l$	$.552^a$	$.704^a$	$.615^a$	$.743^a$	$.655^a$	$.743^a$	$.674^a$	$.629^a$	$.591^a$	$.658^a$	$.729^a$	$.703^a$	$.701^a$	$.806^a$	$.712^a$	$.723^a$	$.735^a$	$.547^a$
$\widehat{\beta}_k$	$.258^a$	$.226^a$	$.092^a$	$.154^a$	$.227^a$	$.191^a$	$.352^a$	$.286^a$	$.182^a$	$.181^a$	$.240^a$	$.184^a$	$.169^a$	$.236^a$	$.269^a$	$.276^a$	$.193^a$	$.323^a$
Labor quality proxied by Griliches' HC																		
$\widehat{\beta}_l$	$.571^a$	$.716^a$	$.626^a$	$.754^a$	$.678^a$	$.704^a$	$.614^a$	$.637^a$	$.597^a$	$.689^a$	$.731^a$	$.707^a$	$.709^a$	$.814^a$	$.723^a$	$.716^a$	$.741^a$	$.503^a$
$\widehat{\beta}_k$	$.260^a$	$.218^a$	$.082^a$	$.155^a$	$.229^a$	$.209^a$	$.335^a$	$.281^a$	$.188^a$	$.158^a$	$.243^a$	$.180^a$	$.175^a$	$.205^a$	$.238^a$	$.276^a$	$.193^a$	$.418^a$
Labor quality proxied by average wage bill																		
$\widehat{\beta}_l$	$.580^a$	$.667^a$	$.625^a$	$.716^a$	$.720^a$	$.727^a$	$.707^a$	$.657^a$	$.620^a$	$.709^a$	$.702^a$	$.699^a$	$.711^a$	$.780^a$	$.740^a$	$.692^a$	$.645^a$	$.527^a$
$\widehat{\beta}_k$	$.251^a$	$.220^a$	$.102^a$	$.136^a$	$.209^a$	$.190^a$	$.269^a$	$.246^a$	$.206^a$	$.241^a$	$.238^a$	$.160^a$	$.152^a$	$.210^a$	$.230^a$	$.281^a$	$.171^a$	$.338^a$
Labor quality proxied by estimated wage bill (Mincer)																		
$\widehat{\beta}_l$	$.547^a$	$.669^a$	$.561^a$	$.668^a$	$.657^a$	$.692^a$	$.603^a$	$.584^a$	$.586^a$	$.676^a$	$.676^a$	$.695^a$	$.662^a$	$.649^a$	$.693^a$	$.716^a$	$.686^a$	$.366^a$
$\widehat{\beta}_k$	$.262^a$	$.274^a$	$.109^a$	$.185^a$	$.217^a$	$.200^a$	$.377^a$	$.323^a$	$.174^a$	$.190^a$	$.269^a$	$.183^a$	$.179^a$	$.358^a$	$.211^a$	$.289^a$	$.207^a$	$.378^a$
Obs.	6084	1146	287	3939	440	7544	722	1620	1974	652	5733	4613	1318	1167	511	2770	2683	332

Note: [a]significant at 1% level, [b]significant at 5% level, [c]significant at 10% level.