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

Alfonso Irarrazabal, Norges Bank   Andreas Moxnes, Dartmouth College

Karen Helene Ulltveit-Moe, University of Oslo and CEPR

Abstract

We investigate to what extent worker heterogeneity explains the well-known wage and productivity exporter premia, employing a matched employer-employee data set for Norwegian manufacturing. The wage premium falls by roughly 50 percent after controlling for observed and unobserved worker characteristics, while the TFP premium falls by 25-40 percent, suggesting that sorting explains up to half of these premia. Recent trade models (e.g. Melitz, 2003) emphasize the role of within-industry reallocation of labor in response to various shocks to the economy. An implication of our work is that aggregate productivity gains due to reallocation may be overstated if not controlling for sorting between firms and workers.

Keywords: Exports, total factor productivity, input quality, firm heterogeneity, linked employer-employee data.

JEL classification: D24, F10, F16, J24, L60

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 sorting between firms and workers.

We already know that exporters perform better than other firms. Their wages are higher; they are larger and 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 therefore seek to go one step further in opening the black box of the exporter premium, and to answer the question of whether exporters are intrinsically more efficient, or whether they merely employ better workers.

Existing productivity analyses of exporters versus non-exporters are typically based on data sets that 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 different measures of labor quality as well as augmented measures of total factor productivity (TFP).

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 controls for observed and unobserved worker characteristics, and to assess the relative importance of labor quality in shaping exporters' wage and productivity premia.

We calculate simple total factor productivity (TFP) measures based on the same type of

---

[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).

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 $25-40$ percent of the exporter productivity premium reflects differences in workforce rather than intrinsic firm quality. Furthermore, we find that roughly half of the exporter wage premium reflects workforce differences, suggesting that sorting between high productivity workers and high productivity firms is important.

Our empirical results establish that in order to assess the impact of various shocks 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 and sorting.

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 three 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 controlling for workforce characteristics. Moreover, we investigate the relationship between exporter premia and sorting. 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 that are related to our work.

In their 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. Following 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).

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

---

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

exception is Fox and Smeets (2010) 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.

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 job tenure (years of experience in current firm) of exporters versus non-exporters 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

---

[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 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.

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.
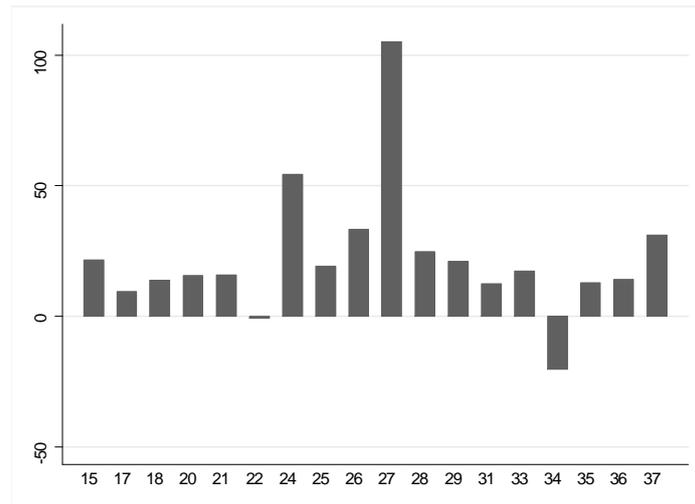
Figure 1: Job tenure. Difference between exporters and non-exporters in %, by industry.
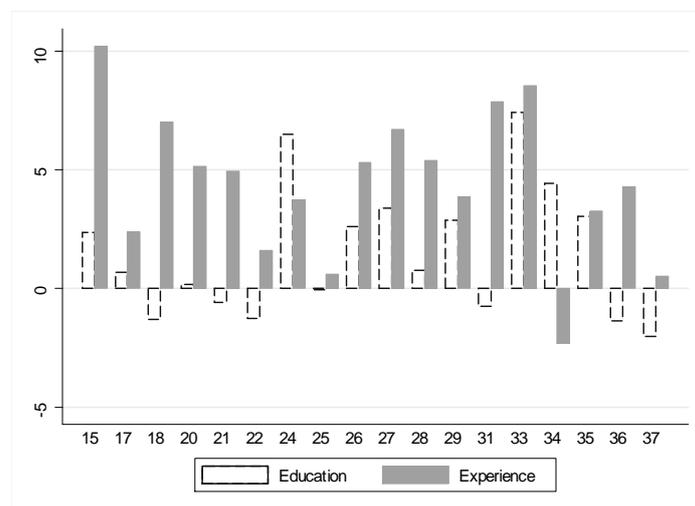
Figure 2: Labor market experience and education. Difference between exporters and non-exporters in %, by industry.

---

[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.

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

$$y_{it} = \beta_0 + \beta_l l_{it}^* + \beta_k k_{it} + \mu_{it} + \eta_{it} \tag{1}$$

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. μ_{it} is unobserved productivity and η_{it} is i.i.d. noise (either measurement error or a shock to productivity which is not forecastable during the period in which labor can be adjusted). Although we do not explicitly include subscripts for industry, we let β_l and β_k vary by industry, at the two digit NACE level.

We follow Olley and Pakes (1996), Ackerberg, Caves and Frazer (2006) and De Loecker (2010) and estimate the production function using a structural proxy estimator. As is well known, the Olley and Pakes (1996) procedure controls for endogeneity in capital and labor by constructing a proxy for μ_{it} from observable variables. Additionally, we allow for the possibility of exporting to affect productivity (learning by exporting), by specifying a process for productivity that depends on past export participation, following De Loecker (2010).[11] Moreover, we adjust their techniques to account for labor quality heterogeneity, and follow a two-step procedure.

First, consider a process for productivity where μ_{it} is determined by lagged productivity and lagged export status indicator e_{it-1},

$$\mu_{it} = g\left(\mu_{it-1}, e_{it-1}\right) + \xi_{it} \tag{2}$$

where ξ_{it} is the news term in the Markov process, uncorrelated with any lagged choice variables of the firm. We follow De Loecker (2010) and include lagged export status in the law of motion, so that exporting can potentially impact future productivity.

Labor is a non-dynamic input, but capital is assumed to be a dynamic input subject to an investment process,

$$k_{it} = \kappa\left(k_{it-1}, i_{it-1}\right). \tag{3}$$

Hence, the capital stock of the firm in period t was determined in period $t-1$, and k_{it} must therefore be uncorrelated with the innovation in the productivity process, ξ_{it}.

---

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

[11] Estimating a restricted model without learning does not change any substantive results in this paper.

The equilibrium investment policy function is then a function of the state variables of the firm, $i_{it} = f_t(\mu_{it}, k_{it}, e_{it})$, where e_{it} is included since the export status of a firm impacts future productivity. Provided that f is strictly increasing in μ_{it}, $\mu_{it} = f_t^{-1}(i_{it}, k_{it}, e_{it})$. The production function can then be written

$$y_{it} = \beta_l l_{it}^* + \phi_t(i_{it}, k_{it}, e_{it}) + \eta_{it} \tag{4}$$

where $\phi_t(i_{it}, k_{it}, e_{it}) = \beta_0 + \beta_k k_{it} + f_t^{-1}(i_{it}, k_{it}, e_{it})$.[12]

In the 1st stage, we estimate (4) by OLS or Non-Linear Least Squares (NLS) depending on the method by which we account for labor quality differences. We approximate ϕ_t by a 3rd 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. From estimating the 1st stage, we obtain an estimate of β_l and ϕ_t, $\widehat{\beta}_l$ and $\widehat{\phi}_t$.

In the 2nd stage, given a guess of the capital coefficient β_k, we can back out unobserved productivity,

$$\widehat{\mu}_{it} = \widehat{\phi}_t - \widehat{\beta}_k k_{it} \tag{5}$$

We can then decompose μ_{it} into its conditional expectation at time $t-1$, $E\left[\mu_{it}|\mu_{it-1}, e_{it-1}\right]$, and a deviation from that expectation ξ_{it}, by estimating by OLS

$$\widehat{\mu}_{it} = g\left(\widehat{\mu}_{it-1}, e_{it-1}\right) + \xi_{it} \tag{6}$$

where we assume that $g()$ is linear, $g() = \gamma + \gamma_\mu \widehat{\mu}_{it-1} + \gamma_e e_{it-1}$.[13] We then form the residual $\widehat{\xi}_{it} = \widehat{\mu}_{it} - \widehat{g}\left(\widehat{\mu}_{it-1}, e_{it-1}\right)$. By the properties of a conditional expectation, the innovation component of the productivity process satisfies

$$E\left[\xi_{it} k_{it}\right] = 0 \tag{7}$$

since capital in t is determined by investment in $t-1$. We also add the following overidentifying restrictions $E\left[\xi_{it} k_{it-1}\right] = E\left[\xi_{it} m_{it-1}\right] = 0$, where m_{it-1} is input usage in $t-1$. The estimate of β_k is then found by minimizing

$$M(\beta_k)' M(\beta_k), \tag{8}$$

where $M(\beta_k)$ is the 3x1 column vector representing the empirical counterpart of the theoretical moments above.

Our measure of total factor productivity is then $tfp_{it} = y_{it} - \beta_l l^* - \beta_k k_{it}$. In the subsequent sections, we construct several variations of tfp_{it}, depending on the treatment of l^*.

As is well known (e.g. Klette and Griliches (1996), Klette (1999), De Loecker (2007) and De Loecker and Warzynski (2010), measures of revenue-based productivity capture both efficiency and mark-ups. Hence, the export productivity premium may also reflect differences in mark-ups across exporters and non-exporters. This bias will occur irrespective of whether l_{it} or l_{it}^*

---

[12]In the next section, we show how l^* is estimated using a set of observable covariates on worker characteristics (the Griliches approach). Due to the added compexity of this step, we chose not to identify both β_l and β_k in the 2nd stage, as in Ackerberg et al (2006).

[13]We could introduce a more flexible functional form, but all substantive results remain largely unchanged in either specification. We present the linear form here due to its ease of interpretation.

(unadjusted or adjusted labor) is chosen as the preferred measure of labor in the production function. Therefore, since the main objective of this paper is to demonstrate that controlling for labor quality *changes* the premium (and not necessarily finding its' level), we have chosen to abstract from this complication here.

4.2 Griliches' measure of human capital

To account for differences in firms' labor stock, we first 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 (2010), 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.[14] For now 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

$$L_{it}^* = z_H L_{it} \left[1 + (\theta_C - 1) x_{Cit} \right] \tag{9}$$

where $\theta_C \equiv z_C/z_H$ is the marginal productivity of college relative to high school graduates, and $x_{Cit} \equiv C_{it} / (C_{it} + H_{it})$ is the number of college graduates relative to the total workforce. Taking logs and substituting (9) into the production function (4) yields

$$y_{it} = \beta_l \left(l_{it} + q_{it} \right) + \phi_t \left(i_{it}, k_{it}, e_{it} \right) + \eta_{it} \tag{10}$$

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

In practice, we are not only distinguishing workers by high school or college degree, but by a vector of worker characteristics. Including many 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.[15] Second, we restrict the proportion of workers in an establishment defined by a demographic group to be constant across all other groups.[16]

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

---

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

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

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

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.[17]

With these assumptions, the quality index becomes:

$$
\begin{aligned}
Q_{it}^{Griliches} = \; & [1 + (\theta_M - 1)\, x_{Mit}] \\
& [1 + (\theta_{E_2} - 1)\, x_{E_2 it} + .. + (\theta_{E_5} - 1)\, x_{E_5 it}] \\
& [1 + (\theta_{X_2} - 1)\, x_{X_2 it} + .. + (\theta_{X_5} - 1)\, x_{X_5 it}] \\
& [1 + (\theta_{T_2} - 1)\, x_{T_2 it} + .. + (\theta_{T4} - 1)\, x_{T_4 it}]
\end{aligned}
\tag{11}
$$

where M denotes share of males in the labor force, while E, X and T denote the education, experience and tenure groups (e.g. $x_{E_2 it}$ 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.

Estimation of equation (10) is carried out with non-linear least squares since the terms in Q_{it} enter non-linearly. Also note that we retrieve estimates of $\widehat{\theta_m - 1}$, so relative marginal productivities are $\widehat{\theta}_m = \widehat{\theta_m - 1} + 1$. After estimation of equation (10), the second stage of the production function methodology is performed, according to Section 4.1, 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 that allows for imperfect substitution between labor types. However, the Cobb-Douglas specification suffers from two problems. First, it can not handle cases where $x_{mit} = 0$, which appears relatively frequently in the data. Second, the estimating equation becomes less tractable.

The workforce characteristics in the data set cover important aspects of worker efficiency, but are 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.

---

[17]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.

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 were not perfectly competitive, we would reckon that wages are likely to be highly correlated with workers' efficiency.[18] As argued by among others Fox and Smeets (2010), 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 model quality adjusted employment as

$$l_{it}^* = \ln w_{it} + \ln L_{it}, \tag{12}$$

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 in equation (4).

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.[19] 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, this 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

$$\ln w_{jt} = \varphi_j + \Psi_{I(j,t)} + x_{jt}\lambda + \varepsilon_{jt} \tag{13}$$

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, φ_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 time-varying exogenous characteristics of individual j, measured relative to their grand means, and ε_{jt} is the statistical

---

[18] 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.

[19] 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.

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.[20] 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, and four, and year dummies. The data are described in more detail in 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 (13), 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 unobservable time-invariant individual characteristics. $x_{jt}\widehat{\lambda}$ is the value of observed time-variant worker characteristics, so their sum is an estimate of the overall value of skills of individual j at time t, independent of any firm-specific effects $\Psi_{I(j,t)}$.

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

$$q_{it}^{Mincer} = \sum_{j:I(j,t)=i} \omega_{jt} \ln \widehat{w}_{jt} \tag{14}$$

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 $l_{it}^* = q_{it}^{Mincer} + l_{it}$, which we substitute into the production function in equation (4), which in turn is estimated according to the methodology in Section 4.1.

5   Results

We estimate the standard and augmented production function, independently for each 2 digit NACE sector, 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 produc-

---

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

tivity and calculate a standard and adjusted exporter premia. We show that the exporter TFP and wage premia are significantly reduced after controlling for worker heterogeneity, suggesting that exporter superiority is not only related to intrinsic firm efficiency but also to superior workers. We address the role of sorting and analyze the relationship between sorting and the wage premium.

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 production function methodology. The other approaches are based on OLS in the first stage. To simplify the presentation, the results in Table 1 are derived from the pooled sample of all manufacturing firms. Note, however, that the subsequent TFP analysis is based on sector-specific estimates (2 digit NACE) of the production function.[21] All standard errors are bootstrapped. Bootstrapping is performed by drawing N firms with replacement, where N is the total number of firms, and constructing a panel following each firm for every year in existence. The standard errors are based on 250 bootstrap iterations.

Table 1: Production function estimates with learning

	PF without Labor quality (LQ) adjustment (1)		PF with LQ adjustment; Griliches HC (2)		PF with LQ adjustment; Estimated wage (3)		PF with LQ adjustment; Average wage (4)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Employment($\widehat{\beta_l}$)	$.670^a$	(.006)	$.678^a$	(.006)	$.640^a$	(.007)	$.670^a$	(.006)
Capitalservices($\widehat{\beta_k}$)	$.310^a$	(.014)	$.304^a$	(.005)	$.330^a$	(.006)	$.280^a$	(.005)
μ lag (γ_μ)	$.37^a$	(.05)	$.37^a$	(.02)	$.40^a$	(.02)	$.49^a$	(.02)
Learning (γ_e)	$.03^a$	(.01)	$.02^b$	(.01)	$.03^a$	(.01)	$.02^a$	(.00)
Number of firm-years	54,110		54,110		54,110		54,110	
Number of firms	12,507		12,507		12,507		12,507	

Notes: Estimates are based on the panel 1996-2005. Standard errors are obtained by bootstrapping.
[a]significant at 1% level, [b]significant at 5% level, [c]significant at 10% level.

We also report the first stage of the production function estimation with quality adjustments a la Griliches for the pooled sample and non-exporters and exporters separately, see Table 2.[22] The first thing to note here is a significant positive monotonic relationship between years of education and marginal productivity. Specifically, the education coefficients rise from 0.17 to 1.18 for the pooled sample, implying that the marginal productivity of workers with 11 or

---

[21]In the Griliches method, the production function is estimated on all manufacturing firms, since lack of variation in human capital variables in a few industries gives very imprecise estimates when estimating per industry.

[22]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.

more years of education is between 17 and 118 percent higher than the group of workers with education less than 11 years. Among exporters the role of education is even more pronounced, with workers with more that 11 years of education being up to 175 percent more productive. This suggests that returns to education are higher among exporters than among non-exporters. This may provide one explanation for why exporters on average employ more educated workers (see Figure 2).

For labor market experience, which by construction is highly correlated with age, our results suggest a non-monotonic – bell-shaped – relationship, for the pooled sample as well as for non-exporters and exporters. Firm tenure does not appear to affect relative productivities when looking at the complete sample.

In sum, the coefficients for Male, Tenure 2-7 years, Tenure 7+ years, all education groups as well as all experience groups except 33+, are significantly (p-value .1 or lower) higher for exporters than for non-exporters.

Table 2: First stage production function estimates with Griliches Human Capital

Griliches HC	All		Non-Exporters		Exporters	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Employment($\widehat{\beta}_l$)	$.678^a$	(.003)	$.679^a$	(.004)	$.683^a$	(.011)
Maleshare	$.025^b$	(.012)	-.023	(.018)	$.106^a$	(.040)
Tenure1-2	$-.144^a$	(.018)	$-.136^a$	(.027)	$-.113^c$	(.067)
Tenure2-7	-.010	(.019)	.000	(.030)	$.131^c$	(.080)
Tenure7+	.001	(.020)	.019	(.031)	$.131^a$	(.081)
Education11-12	$.173^a$	(.017)	$.170^a$	(.026)	$.237^a$	(.073)
Education13-14	$.387^a$	(.020)	$.333^a$	(.030)	$.693^a$	(.089)
Education15-16	$.987^a$	(.045)	$.788^a$	(.066)	1.745^a	(.185)
Education17+	1.182^a	(.051)	$.966^a$	(.078)	1.316^a	(.178)
Experience 13-19	$.137^a$	(.021)	$.120^a$	(.031)	$.248^a$	(.087)
Experience 20-25	$.182^a$	(.021)	$.175^a$	(.033)	$.229^a$	(.086)
Experience 26-32	$.223^a$	(.021)	$.218^a$	(.032)	$.343^a$	(.082)
Experience 33+	$.179^a$	(.022)	$.199^a$	(.036)	$.204^a$	(.086)
Number of firm-years	54,110		24,259		11,422	

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

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 reports interim results from the two-way fixed effects wage model (Mincer). 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: 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
Obs	15.7 mill
std(θ_i)	.62
std($\Psi_{J(i,t)}$)	.25
corr($\Psi_{J(i,t)}, \theta_i$)	.03

We compare the quality indices produced by the two methods – Griliches and Mincer. A simple indicator is the correlation between the $q_{it}^{Griliches}$ and q_{it}^{Mincer}, obtained from equations (11) and (14). Using all firms in the sample, we find that the correlation is 0.18.[23] Truncating the sample by dropping firms with less than 20 employees eliminates a fair amount of noise and increases the correlation to 0.41.[24] The fact that the correlation is less than one, partly reflects that, even after controlling for firm effects, wages only imperfectly reflect marginal productivities in the Norwegian labor market.

Our empirical methodology enables us to account for the potentially endogenous relationship between exporting and productivity. The endogenous productivity process in equation (6) relates current productivity to lagged productivity and export status. The function is precisely estimated, and for the pooled sample, we find that exporting increases firms' productivity by around 3 percent (Table 1). Looking at the different industries, the impact of exporting on productivity varies from just beyond 2 percent up to almost 5 percent. These results are robust to whether we use productivity measures adjusted for labor quality or not. The magnitudes are also similar to the findings in De Loecker (2010).

Finally, we use sector-specific estimates of the production function to calculate total factor productivity residuals. Total factor productivity is calculated as

$$tfp_{it}^v = y_{it} - \widehat{\beta}_l^v l_{it}^{*v} - \widehat{\beta}_k^v k_{it} \tag{15}$$

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.

---

[23] The corresponding correlation between $q_{it}^{Griliches}$ and actual wages (ln w_{it}) is 0.32. The correlation between q_{it}^{Mincer} and ln w_{it} is 0.35.

[24] The corresponding correlation between $q_{it}^{Griliches}$ and actual wages (ln w_{it}) is 0.66. The correlation between q_{it}^{Mincer} and ln w_{it} is 0.50.

5.2 Exporter premia

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

$$z_{it} = \beta_k + \alpha_t + \rho Ex_{it} + \gamma L_{it} + \varepsilon_{it} \qquad (16)$$

where z_{it} is tfp_{it}^v as well as other firm characteristics, Ex_{it} is an exporter dummy, β_k denotes industry fixed effects, and α_t denotes year dummies. Industry fixed effects are based on 4-digit nace industries. Hence, $\exp(\rho)$ measures the exporter premium in percent within the same industry-year and for same firm size. The premia we consider in Table 4 are labor productivity, TFP (unadjusted and quality adjusted), wages, capital stock (total and split into structures and machinery), profits, average tenure, education level, labor market experience, and quality indices q_{it}^{Mincer} and $q_{it}^{Griliches}$. When pooling the sample over all years, we cluster standard errors by firm. The two last columns show results for the 1996 and 2005 cross-section.

Productivity: In line with previous studies we find that exporters are more productive. The unadjusted TFP premium is somewhat lower than what has been found in the U.S. (see e.g. 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 24 percent in the Griliches case, and more than 40 percent when we adjust for labor quality using average or predicted wages. We can 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, and calculated the associated exporter premium.[25] Our exporter premium results also appeared robust to alternative assumptions about labor substitutability. Looking at the different cross-sections separately, we continue to find that the TFP premium is reduced after correcting for labor quality differences, and that the reduction is in most cases statistically significant.[26]

Other premia: 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 ($q_{it}^{Griliches}$) and the quality measure developed on the basis of the Mincer regression (q_{it}^{Mincer}).

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

---

[25] The model is presented in detail in the appendix. Results are available upon request.

[26] Estimating the TFP premium separately for every year in the sample yields a significant reduction in the unadjusted to Mincer adjusted premium in 7 out of 10 years (p-value 0.1 or lower).

of automation.

Table 4: Exporter premia

	Export premia 1996-2005*			Export premia 1996	Export premia 2005
	in %	Coef. (ρ)	S.E.	in %	in %
Labor productivity	16.79^a	$.155^a$	(.008)	19.51^a	16.92^a
TFP unadjusted	6.73^a	$.065^a$	(.007)	8.80^a	7.48^a
TFP adjusted; Griliches HC	5.13^a	$.050^a$	(.007)	6.72^a	5.31^a
TFP adjusted; Estimated wage	3.77^a	$.037^a$	(.007)	5.66^a	3.80^a
TFP adjusted; Average wage	3.97^a	$.039^a$	(.006)	6.91^a	3.71
Capital stock per worker	34.99^a	$.300^a$	(.014)	37.95^a	32.35^a
Structures per worker	16.33^a	$.151^a$	(.044)	20.79^a	25.33^a
Machinery per worker	32.44^a	$.281^a$	(.022)	39.22^a	22.50^a
Profit margin	44.23^a	$.366^a$	(.020)	50.82^a	48.40^a
Tenure	4.21^a	$.041^a$	(.012)	2.06	2.96
Wage	5.42^a	$.053^a$	(.005)	4.03^a	6.68^a
Years of education	$.86^a$	$.008^a$	(.002)	$.75^a$	1.55^a
Labor market experience	2.92^a	$.029^a$	(.004)	1.89^a	2.44^a
Quality index 1 ($q_{it}^{Griliches}$)	3.21^a	$.032^a$	(.003)	3.14^a	4.63^a
Quality index 2 (q_{it}^{Mincer})	2.43^a	$.024^a$	(.005)	1.22^a	4.35^a
Industry dummies (nace 4)	Yes			Yes	Yes
Year dummies	Yes			No	No
Number of firm-years	73,842			6,652	7,496

Note: *Estimates are based on the panel 1996-2005. Exporter premium in % $= (e^\rho - 1)100$
^{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.

5.3 Wages and Sorting

The results so far highlight that exporters are more productive, more profitable and pay higher wages. In this section, we first ask how much of the exporter wage premium is due to sorting (compositional effects), versus how much is due to exporters paying more for the same type of labor (due to frictions in the labor market such as search frictions, bargaining or rent sharing). Second, given that sorting explains less than 100 percent of the wage premium, we ask whether certain labor groups (e.g. PhDs) are relatively better paid among exporters than non-exporters.

The exporter premium for the Mincer quality index q_{it}^{Mincer} provides a measure of the wage premium after firm fixed effects have been removed. Hence, it follows from Table 4 that the wage premium is reduced from 5.42 to 2.43 percent after removing firm fixed effects. In other words, 45 percent (2.43/5.42) of the wage premium can be ascribed to worker characteristics (sorting) rather than firm characteristics. Alternatively, we can calculate the wage premium that is due to firm characteristics exclusively. Within our framework, this is done by calculating the exporter premium for the firm wage fixed effect from the Mincer estimation ($\Psi_{I(j,t)}$), see (13). We find that the exporter premium for the firm fixed effect is 2.2 percent. This suggests that roughly 60 percent $(1 - 2.2/5.42)$ of the wage premium is due to sorting, roughly in line with the results above.

We also use the estimated firm and worker fixed effects from the Mincer approach to calculate the sorting measure proposed by Lopes de Melo (2009). Lopes de Melo suggests an improved measure of sorting by calculating the correlation between a worker fixed effect and the average worker fixed effects of his coworkers, $corr\left(\varphi_j, \varphi_j^{other}\right)$, where φ_j^{other} is the average worker fixed effect for j's coworkers. We find that the Lopes De Melo correlation is about 0.4, close to findings from Brazil and Denmark reported by Lopes de Melo. All in all, this suggests that sorting plays a major role also in the Norwegian labor market.

Second, we proceed by decomposing the wage premium among different labor groups. We follow Hellerstein et al (1999) and write total firm-level log wages as

$$
\begin{aligned}
\ln W_{it} \;=\; & a + \ln L_{it} + \ln\left[1 + (\lambda_M - 1)\,x_{Mit}\right] \\
& \left[1 + (\lambda_{E_2} - 1)\,x_{E_2 it} + .. + (\lambda_{E_5} - 1)\,x_{E_5 it}\right] \\
& \left[1 + (\lambda_{X_2} - 1)\,x_{X_2 it} + .. + (\lambda_{X_5} - 1)\,x_{X_5 it}\right] \\
& \left[1 + (\lambda_{T_2} - 1)\,x_{T_2 it} + .. + (\lambda_{T4} - 1)\,x_{T_4 it}\right] + \varepsilon_{it}
\end{aligned}
\tag{17}
$$

where a is the log wage of the reference group, which is simply a constant. The interpretation of the coefficients is similar to the productivity case, e.g. λ_{E_5} captures the wage among the most highly educated relative to the reference group. We estimate (17) for exporters and non-exporters separately and report the results in Table 5. For all groups except Education 11-12 years, λ is higher among exporters than non-exporters. The difference is especially large for high education. This suggests that, after controlling for sorting, the aggregate exporter wage premium is partly explained by higher wages to the most highly skilled workers.

Table 5: Relative wages for different groups: Exporters and non-exporters

	Relative wages (λ)	
	Exporters	Non-Exporters
Maleshare	0.46^a	0.28^a
Tenure1-2	-0.03	$-.04^a$
Tenure2-7	0.06^b	0.02
Tenure7+	0.06^b	0.03^c
Educ11-12	0.03^b	0.09^a
Educ13-14	0.50^a	0.32^a
Educ15-16	0.99^a	0.62^a
Educ17+	1.24^a	0.71^a
Exper 13-19	0.39^a	0.25^a
Exper 20-25	0.62^a	0.32^a
Exper 26-32	0.37^a	0.28^a
Exper 33+	0.59^a	0.42^a
Obs	13,829	35,432

Note: Estimates are based on the panel 1996-2005.
[a]significant at 1% level, [b]significant at 5% level, [c]significant at 10% level.

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 and wage premia, we use a unique data set of firms, worker characteristics and trade. This allows us to calculate improved measures of total factor productivity that 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 and pay higher wages, consistent with models of firm heterogeneity and input quality such as Verhoogen (2008).

We find that both the wage and productivity premia fall after controlling for workforce characteristics. The wage premium falls by roughly 50 percent, and the exporter TFP premium falls by between $25 - 40$ percent, depending on the method used, suggesting that sorting is an important mechanism in the Norwegian manufacturing sector. Furthermore, 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 exit.

References

[1] Abowd, John M., Creecy, Robert H. and Francis Kramarz, 2002, "Computing person and firm effects using linked longitudinal employer-employee data", LEHD technical paper no.09/2002

[2] Abowd, John M., Kramarz, Francis and David N. Margolis, 1999, "High Wage Workers and High Wage Firms", Econometrica, 67, 251-333

[3] Bernard, Andrew B., Jensen, J. Bradford and Robert Z. Lawrence, 1995, "Exporters, Jobs, and Wages in U.S. Manufacturing: 1976-1987", Brookings Papers on Economic Activity. Microeconomics, 1995, 67-119

[4] Bernard, Andrew B. and J. Bradford Jensen, 1999, "Exceptional exporter performance: Cause, effect, or both?", Journal of International Economics, 47, 1-25

[5] Bernard, Andrew B., Jensen, J. Bradford, Redding, Stephen J. and Peter K. Schott, 2007, "Firms in international trade", Journal of Economic Perspectives 21, 105-130

[6] De Loecker, Jan and Fredric Warzynski, 2010, "Markups and Firm-level Export Status", NBER Working Paper no.15198, forthcoming, American Economic Review.

[7] De Loecker, Jan, 2010, "A note on detecting learning by exporting", Mimeo, Princeton University

[8] De Loecker, Jan, 2007, "Product Differentiation, Multi-Product Firms and Estimating the Impact of Trade Liberalization on Productivity", NBER Working Paper no. 13155, forthcoming, Econometrica

[9] Fox, Jeremy T. and Valérie Smeets, 2010, "Does Input Quality Drive Measured Differences in Firm Productivity?", forthcoming International Economic Review.

[10] Frías, Judith A., Kaplan, David S. and Eric A. Verhoogen, 2009, "Exports and Wage Premia: Evidence from Mexican Employer-Employee Data", Mimeo, Columbia University

[11] Griliches, Zvi, 1957, "Specification Bias in Estimates of Production Functions", Journal of Farm Economics, 39, 8-20

[12] Hellerstein, Judith K. and David Neumark, 2006, "Production Function and Wage Equation Estimation with Heterogeneous Labor: Evidence from a New Matched Employer-Employee Data Set", in Hard to measure Goods and Services: Essays in Honor of Zvi Griliches, University of Chicago

[13] Hellerstein, Judith K., Neumark, David and Kenneth R. Troske, 1999, "Wages, Productivity, and Worker Characteristics: Evidence from Plant-Level Production Functions and Wage Equations", Journal of Labor 17, 409-446

[14] Klette, Tor Jakob, 1999, "Market Power, Scale Economies and Productivity: Estimates from a Panel of Establishment Data", Journal of Industrial Economics, 47, 451-476

[15] Klette, Tor Jakob and Zvi Griliches, 1999, "The inconsistency of common scale estimators when output prices are unobserved and endogenous", Journal of Applied Econometrics, 11, 343 - 361

[16] Lopes de Melo, R., 2009, "Sorting in the labor market: theory and measurement", mimeo, University of Chicago

[17] Mayer, Thierry and Gianmarco I. P. Ottaviano, 2007, "The happy few: the internationalisation of European firms", Bruegel Blueprint 3

[18] Melitz, Marc, 2003, "The impact of trade on intra-industry reallocations and aggregate industry productivity", Economectrica, 71, 1695-1725

[19] Munch, Jakob Roland and Jan Rose Skaksen, 2008, "Human capital and wages in exporting firms", Journal of International Economics 75, 363-372

[20] Olley, G. Steven and Ariel Pakes, 1996, "The Dynamics of Productivity in the Telecommunications Equipment Industry," Econometrica, 64, 1263-1297

[21] Pavcnik, Nina, 2002, "Trade liberalization, exit and productivity improvements: evidence from Chilean plants", Review of Economics Studies, 69, 245-276

[22] Raknerud, Arvid, Rønningen, Dag and Terje Skjerpen, 2004, "Documentation of the capital database", Statistics Norway Documents 2004/16

[23] Rosen, Sherwin, 1983, "A Note on Aggregation of Skills and Labor Quality." Journal of Human Resources 18, 425-431

[24] Schank, Thorsten, Schnabel, Claus and Joachim Wagner, 2007, "Do exporters really pay higher wages? First evidence from German linked employer-employee data", Journal of International Economics, 72, 52-74

[25] Shaw, Kathryn and Edward P. Lazear, 2008, "Tenure and output", Labour Economics, 15, 704-723

[26] Van Biesebroeck, Johannes, 2007, "Wage and productivity premiums in sub-Saharan Africa", NBER Working Paper no. 13306

[27] Eric A. Verhoogen, 2008, "Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector", Quarterly Journal of Economics, 123, 489-530

[28] Wagner, Joachim, 2007, "Exports and Productivity: A Survey of the Evidence from Firm-level Data", World Economy 30: 60-82

[29] Welch, Finis, 1969, "Linear Synthesis of Skill Distribution", Journal of Human Resources, 4, 311-327.

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 (13) 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),[27] 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

---

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

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

$$l_{it}^* = \sum_{m \in \Omega} z_m l_{mit} \tag{18}$$

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. $x_M = L_{MC}/(L_{MC} + L_{FC}) = L_{MH}/(L_{MH} + L_{FH})$. Then equation (18) can be rewritten as

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

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,

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

l^* becomes

$$l_{it}^* = \alpha_1 \ln x_{Mit} + \alpha_2 \ln x_{Fit} + \sum_{m \in \Omega_{-S}} \alpha_m l_{mit} \tag{19}$$

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 (4) together with (19), using the Olley-Pakes procedure, by sector. Next we calculate adjusted TFP indices and construct the adjusted TFP premium, using (16). The results are very close to those obtained in our base, and are available upon request from the authors.

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