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HETEROGENEOUS FIRMS OR HETEROGENEOUS WORKERS? IMPLICATIONS FOR THE EXPORTER PREMIUM AND THE IMPACT OF LABOR REALLOCATION ON PRODUCTIVITY

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ABSTRACT

Heterogeneous firms or heterogeneous workers? Implications for the exporter premium and the impact of labor reallocation on productivity

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 stark 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 up to 67 percent of the exporter premium reflects differences in workforce rather than true efficiency. Simulating the labor dynamics proceeding firm exits, we illustrate that the benign impact on aggregate productivity from firm exits may be reduced because of worker reallocation.

JEL Classification: D24, F12, F14 and F16
Keywords: exporters, firm heterogeneity, labor reallocation, productivity measurement and worker heterogeneity

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1 Introduction

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] 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 as well as background 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. Our hypothesis is that one reason why exporters are more productive is simply because they employ more productive workers.

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, and to answer the question of whether exporters are really intrinsically more efficient, or whether they merely employ better workers. We do this by calculating augmented measures of total factor productivity (TFP) that includes different measures of labor quality. Our findings are important for the assessment of gains from trade: In trade models with heterogeneous firms, trade liberalization gives aggregate productivity gains because the least productive firms are squeezed out of the market and the workers are reallocated towards the best performing firms. But the positive reallocation effect relies on the stark assumption that exporters' superior performance reflects intrinsic firm quality. 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.

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, tenure, and location of residence 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

[1]See Bernard, 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).

firms, and augmented TFP measures where we adjust for differences in labor quality. By comparing the results on TFP, we find that up to 67 percent of the exporter productivity premium reflects differences in workforce rather than intrinsic firm quality. On average, the exporter TFP premium falls by 30 percent after controlling for workforce characteristics.

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, may be smaller once we account for worker heterogeneity. To get a better grasp of how labor reallocation affects productivity we perform a simple quantitative exercise using detailed employer-employee data on worker flows. The simulations confirm the empirical results, and indicate less gains from intra-industry reallocation 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 estimate. Section 6 presents a simple simulation model, evaluating the impact of our results on reallocation and aggregate productivity, while section 7 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

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

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.

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 popu-

[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.

lation 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 across industries (see Table 8 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 two alternative approaches to model and quantify labor quality, (i) Griliches' human capital approach, and (ii) using the estimated wage bill as a proxy for quality. But before describing these two 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 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.

[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.

[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.

- 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 quality heterogeneity, and follow a three-step procedure: 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

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

where $\phi_t (k_{it}, i_{it}) = \beta_0 + \beta_k k_{it} + f_t^{-1}(i_{it}, k_{it})$. First 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 regressors are a $4th$ order polynomial expansion along with year dummies.

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

where $\chi_t = 1$ if the firm is present in year t. Finally we use the estimates of β_l, $\phi_t (k_{it}, i_{it})$ 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.

[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.

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.[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

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

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

[12] The sensitivity of this approach is discussed below. Rosen (1983) describes issues related to this specification of labor input.

[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.

are (T_1) <1 year, (T_2) 1-2 years, (T_3) 2-7 years, (T_4) more than 7 years.[15]

In addition we include a geography variable that measures the density of exporting skills in a location, calculated as the fraction of employees in a worker's municipality that are working for export firms. The geography variable allows us to account for the importance of localization of exporting skills. The basic idea is that exporting requires specific skills and attitudes that are rather general in nature (i.e. not industry specific), and which are best acquired by the interaction with other people also active in the export sector. Hence, our working hypothesis is that geographical proximity to other workers with export experience is important.[16]

With these assumptions, the quality index becomes:

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

where M and S denote the male and exporting skills categories, 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 $\widehat{\theta_m - 1}$, so relative marginal productivities are $\widehat{\theta}_m = \widehat{\theta_m - 1} + 1$. 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. Therefore, we also estimate the model based on a slightly different functional form of Q_{it}, following Welch (1969) and Fox and Smeets (2008):

$$Q_{it}^{add} = 1 + (\theta_M - 1)\,x_{Mit} + (\theta_S - 1)\,x_{Lit} + \;..$$

i.e. we simply add the contribution of each labor quality measure.

[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.

[16] For details on the construction of the exporting skills variable, see section A.2 in the Appendix.

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 section below we describe an alternative method of backing out worker quality, where we control for both observed and unobserved skill.

4.3 The estimated wage bill as a proxy for labor quality

Our second approach is to estimate labor quality by using information about wages from every employer-employee spell. If one is willing to assume that the labor market is competitive and that wages reflect marginal products, a simple estimator of workforce quality is firm-level average wages. Even if the labor market is not perfectly competitive, we would reckon that wages are likely to be highly correlated with workers' efficiency.[17] 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.[18] 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, predicted wages, averaged over all employees within a firm, are used as a proxy for workforce quality when we estimate the production function.

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

$$\ln w_{jt} = \varphi_j + \Psi_{I(j,t)} + x_{jt}\lambda + \varepsilon_{jt} \tag{8}$$

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

[17] Shaw and Lazear (2008) 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.

[18] 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.

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.[19] 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 (8), we calculate $\ln \widehat{w}_{jt} = \widehat{\varphi}_j + x_{jt}\widehat{\lambda}$. The estimated person effects φ_j are estimates of the value of all time-invariant individual characteristics, including both unobserved and observed skill. $x_{jt}\widehat{\beta}$ 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.

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

$$\ln \widehat{w}_{it} = \sum_{j:I(j,t)=i} \omega_{jt} \ln \widehat{w}_{jt} \tag{9}$$

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.

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

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) and the estimated wage approach (column 3). 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 two approaches are based on OLS. 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 9).

[Table 1]

The coefficients for employment and capital are significant and positive in all cases. Most labor characteristics that we have included appear to have a significant influence on a firm's production. 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. Interestingly, the novel exporting skills density variable – measuring the effect of proximity to workers with exporting skills is significant and positive.

Table 2 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 2]

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 0.22. Truncating the sample by dropping firms with less than 20 employees eliminates a fair amount of noise and increases the correlation to 0.41. 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.

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

$$tfp_{it}^{v} = y_{it} - \widehat{\beta}_{l}^{v} l_{it}^{*v} - \widehat{\beta}_{k}^{v} k_{it} \qquad (10)$$

where superscript v denotes the chosen production function specification, subscript i still denotes the firm, and t the year. TFPs are calculated for the model without quality adjustment, for Griliches quality model and for the estimated wage model.

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:

$$z_{it} = \alpha_t + \rho_t Ex_{it} + \gamma_t L_{it} + \sum_k \kappa_{tk} Ind_k + \varepsilon_{it} \tag{11}$$

where z_{it} is tfp_{it}^q as well as other firm characteristics, Ex_{it} is an exporter dummy, Ind_k is a NACE 2 digit industry dummy. OLS is performed separately on each cross-section of the panel. Hence, $\exp(\rho)$ measures the exporter premium in percent within the same sector and for same firm size. The firm variables we consider are labor productivity, TFP calculated on basis of a simple production function as well as quality adjusted production functions, capital stock and profits. We also estimate exporter premia for average tenure, education level, labor market experience, wages (actual and predicted) as well as the quality index Q_{it}.

Figures 3 and 4 summarize the results for TFP. The horizontal axis indicates which year the estimates refer to and the vertical axis shows the exporter TFP premium in percent (e^{ρ_t}). The solid lines show the unadjusted and adjusted premia. The Griliches adjustment is used in Figure 3 and the Mincer adjustment is used in Figure 4. 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 or the estimated wage bill, the exporter premium is reduced. Hence, the exporter premium does not only reflect intrinsic firm differences, with exporters being the superior ones, but also differences in the labor force. Averaging across years and industries, the mean reduction in the exporter premium is 30 percent, both in the Griliches and Mincer case. The dotted lines indicate the 95 percent confidence intervals of the estimated coefficients, and the stars on the x-axis show whether the *difference* between the unadjusted and adjusted coefficient is significant.[20] The hypothesis that the coefficients are equal is rejected for a majority of the years under the Mincer adjustment, while under the Griliches adjustment the results are slightly less robust.

[Figure 3]

[Figure 4]

Table 3 summarizes the different exporter premia for the 1996, 2000 and 2005 cross-sections. In line with previous studies we find that exporters have higher profits, are more capital intensive and pay higher wages. But what our matched employee-employer data set also reveals is that exporters are not only more capital intensive, but they also have a labor force that differs from other firms. Their workers are more experienced, have higher education and, to a certain extent, they have longer tenure. This is also reflected by the two summary measures of workforce quality (Q_{it} and $\ln \widehat{w}_{it}$) which are higher for exporters than for non-exporters.

[20] Formally, we perform a Wald test whether $\rho_t^{\text{griliches}} = \rho_t^{\text{mincer}}$. * = 0.1 level, ** = 0.05 level.

[Table 3]

We proceed by splitting the results on exporter productivity premium by sector. Table 4 shows that in 11 out of 18 industries the exporter TFP premium is reduced if we adjust for differences in the labor stock. The exporter premium shrinks by between 15 and 70 percent once we account for worker heterogeneity. The results differ somewhat depending on whether TFP is adjusted using the estimated wage (Mincer) approach or the Griliches approach. But we observe that in the industries experiencing a significant reduction in the exporter TFP premium when we adjust for quality, the reduction is supported by the Mincer as well as Griliches approach. 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)[21]. These industries have in common that they are among the most skill intensive industries in Norwegian manufacturing. Once we account for differences in the labor stock in these industries the exporter TFP premium falls by roughly 50 percent (averaged across the three industries).

[Table 4]

To check the robustness of our results, we also re-calculated TFP by sector and estimate the associated exporter premium by using an the alternative additive form aggregation Q_{it}^{add} to adjust for differences in human capital. The reduction in the TFP premium, going from the unadjusted to the adjusted model, is in this case 29 percent, close to the findings in the baseline Griliches model.[22] We therefore conclude that the functional form of Q_{it} is not important for the quantitative results in this paper.

6 Heterogeneous workers, reallocation and productivity

In models with heterogeneous firms aggregate productivity gains from firm exit arise because exitors are less productive than continuing firms (Melitz, 2003). Our empirical findings show, however, that intra-firm differences in productivity is not only related to intrinsic firm efficiency, but also to heterogenous workers.

In this section we perform a quantitative exercise to measure the effect of worker reallocation on continuing firms and thus on aggregate industry productivity. Using our empirical estimates on labor quality from section 5, we compare the change in predicted aggregate labor productivity over a five years period for (i) the benchmark case where we abstract from worker heterogeneity with (ii) the case where heterogenous workers and the specific labor dynamics following the exit of firms are accounted for (i.e. tracing the movement of workers previously hired by exit firms). It is, however, important to stress that this is a rather rough exercise, since we include the whole population of manufacturing firms – not only exporters – and we do not discuss the reasons for firm exit.

Let us start by reviewing the numbers for labor productivity in 1997, splitting firms into two groups: those that are still present five years later – in 2002, i.e. the continuers; and those that

[21] Other transport equipment primarily refers to shipbuilding.
[22] Results are available upon request.

have exited by the time we reach 2002, the exitors. Table 5 shows that labor productivity of exiting firms was, as we would have expected, lower than that of continuing firms. Accounting for size, this picture become even clearer. All else being equal, firms' exit therefore raise aggregate productivity in the manufacturing sector.

[Table 5]

6.1 The experiment

Based on the groups of exiting and continuing firms defined above, we identify workers that were employed in an exiting firm in 1997 and moved (reallocated) to a continuing firm within manufacturing in 2002. In order to focus exclusively on input quality and worker reallocation, we keep firm employment, capital stock and total factor productivity constant at their 1997-level.

We compute predicted labor productivity (value added per worker), using parameter estimates from the Griliches human capital approach,[23]

$$\mu_{it} = \beta_0 + \beta_l \left(l_{i1997} + \ln Q_{it} \right) + \beta_k k_{i1997} + tfp_{i1997} - l_{i1997} \tag{12}$$

where the quality index Q_{it} is defined in equation (7) and $t = 1997, 2002$. In 1997, Q_{it} is simply computed by using the actual employment shares (x_{mit}) together with the estimated coefficients (θ_m). In 2002, Q_{it} is constructed by re-calculating the employment shares x_{mit} based on the flow of workers from the exit firms to the incumbents. Therefore, for each firm receiving workers, a change in labor productivity will only reflect movements in the quality index Q_{it}. Finally, we compute simple and weighted average productivity for those firms receiving workers.[24]

To clarify the exercise, consider the case in which firm i receives a worker with 13 years of education in 2002. The addition of an educated worker to firm i changes the values of x_{mit}, raising the proportion of educated workers in firm i and therefore altering the quality index Q_{it}. Q_{it} can increase or decrease depending on the average education level in firm i before the arrival of the new worker.

There are some caveats in the analysis. First, we focus exclusively on the effect of exit reallocation, neglecting changes in the quality composition of the labor force coming from expanding or contracting firms. Second, there are no general equilibrium effects, since we disregard the effect of workers leaving the manufacturing industry.

6.2 The productivity effects of worker reallocation

Table 6 provides characteristics of the workers employed in manufacturing in 1997. In terms of education and experience, workers reallocated to continuing firms are more educated and less experienced than workers in continuing firms. Note also, that workers switching to other manufacturing firms are on average more educated and experienced than those workers who leave the manufacturing sector.

[23] For simplicity, we use parameters estimated for the full sample of all manufacturing industries.

[24] Weighted average productivity is constructed as $\mu_t = \sum_i s_{i1997} \mu_{it}$, where s_{i1997} are employment weights s_{it} based on the year 1997.

[Table 6]

Table 7 describes how average labor productivity μ_t is affected once we account for heterogeneous workers reallocating from exiting firms. 24 percent of the continuing firms received workers from the exitors. We report productivity gains accruing to these firms from the worker reallocation based on three different scenarios: When we account for both the education and experience of the workers to affect the Q_{i2002} for the continuing firms receiving workers, weighted productivity declines by 0.02 percent. The other two columns show the changes if we allow only education or experience to affect labor quality. If we only account for differences in experience, we observe drop in productivity of 0.04 percent. Employees in exiting firms in 1997 had lower experience than average (as seen in Table 6). As a consequence, their reallocation to incumbents decreases the productivity of firms that hired them. Finally, in the case where we assume that only the education of the workers reallocated mattered, the effect on weighted productivity is positive, due to the arrival of more educated workers. Comparing these effects with the productivity growth due to firm exit (0.8 percent growth from "all firms" to "continuing firms" in Table 5) we find that allowing for worker reallocation will reduce reallocation gains by roughly $2-3$ percent.

[Table 7]

Figure 5 depicts the distribution of changes in productivity for firms in the sample. Clearly, there is substantial heterogeneity, with some firms experiencing substantial productivity growth after the reallocation, while others experiencing productivity slowdown.

[Figure 5]

In summary, our simple simulation exercise shows that the composition of worker characteristics matters when studying the effect of firm exit and reallocation on productivity. Although we obtain small changes on average, the firm-level change in labor productivity is significant. Finally, we note that the results obtained here could potentially be different for other countries and for other time periods.

7 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 stark assumption that exporters' superior performance is 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, our results indicate that up to 67 percent of the exporter productivity premium may reflect differences in workforce rather than differences in true efficiency. On average, the exporter TFP premium falls by 30 percent after controlling for workforce characteristics. This tells us 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. Moreover, in order to assess the impact of fiercer international competition and firm exit on aggregate productivity, a simple simulation exercise underscores the point, that we need to 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 exporting skills density$_{it}$ variable

First find the share of workers in municipality k working in exporter firms:

$$\alpha_{kt} = \frac{1}{n_{kt}} \sum_{j \in \Omega_{kt}} I\left[j \text{ employed in export firm at } t\right]$$

where n_{kt} is the number of workers in k, Ω_{kt} is the set of workers in k and $I[]$ is an indicator function. Re-index α_{kt} to α_{jt} meaning the fraction in person j's municipality. Then take the average for all workers in firm i,

$$\text{exporting skills density}_{it} \equiv x_{\text{Si}\,t} = \frac{1}{n_{it}} \sum_{j \in \Delta_{it}} \alpha_{jt}$$

where n_{it} is the number of workers in firm i, Δ_{it} is the set of workers in i. If all workers are living in the same municipality as the firm, then exporting skills density$_{it}$ will represent the fraction of workers in the firm's municipality that is employed by exporters.

A.3 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 (8) 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.4 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),[25] 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.5 Tables

[Table 8]

[Table 9]

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

Table 1: Olley-Pakes production function estimates

	(1) Without Labor Quality adjustment		(2) Labor Quality proxied by Griliches HC		(3) Labor Quality proxied by estimated wage	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Employment($\widehat{\beta}_l$)	.687[a]	(.003)	.690[a]	(.003)	.658[a]	(.003)
Capitalservices($\widehat{\beta}_k$)	.205[a]	(.004)	.209[a]	(.004)	.215[a]	(.004)
Maleshare			.044[a]	(.014)		
Tenure1-2			-.083[a]	(.035)		
Tenure2-7			-.008	(.036)		
Tenure7+			.006	(.017)		
Education11-12			.098[a]	(.020)		
Education13-14			.258[a]	(.021)		
Education15-16			.970[a]	(.054)		
Education17+			1.206[a]	(.061)		
Experience 13-19			.202[a]	(.028)		
Experience 20-25			.233[a]	(.028)		
Experience 26-32			.273[a]	(.028)		
Experience 33+			.200[a]	(.028)		
Export skills density			.516[a]	(.040)		
R-squared	.91		.92		0.91	
Number of obs.	43535		43535		43535	

Note: All sectors pooled. Q_{it}=1 defines the base case and denote the firm with only males, only workers with tenure<1 year, only workers with education<11 years, only workers with experience <13 years and spillover_{it}=0. Hence, male, tenure 0-1, experience 0-13 and edu 0-11 are the omitted categories. [a]significant at 1% level, [b]significant at 5% level, [c]significant at 10% level.

Table 2: 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 3: Exporter premia

	1996	2000	2005
Labor productivity	18.4[a]	18.4[a]	15.2[a]
TFP unadjusted	10.8[a]	10.8[a]	8.0[a]
TFP adjusted with Griliches human capital	8.5[a]	9.3[a]	6.1[a]
TFP adjusted with Mincer estimated wage	9.3[a]	8.1[a]	4.6[a]
Capital stock per worker	37.2[a]	35.1[a]	34.7[a]
Profit margin	44.8[a]	44.9[a]	41.2[a]
Tenure	1.6	3.0	5.7[a]
Years of education	0.6[c]	0.7[a]	1.5[a]
Labor market experience	2.4[a]	3.2[a]	4.0[a]
Quality index 1 (Q_{it})	2.8[a]	1.8[a]	2.1[a]
Quality index 2 ($\ln\widehat{w}_{it}$)	1.5	3.6[a]	4.6[a]
Additional covariates:			
Industry dummies (nace 2)	Yes	Yes	Yes
Log employment	Yes	Yes	Yes
N	6679	7460	7522

Note: TFP is calculated by using Olley-Pakes and industry specific coefficients.
[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 4: Exporter TFP premia by sector

Industry	TFP Unadjusted	TFP Mincer	TFP Griliches
Food products and beverages	13.2[a]	8.9[a]	10.1[a]
Textile products	7.3[a]	3.2	8.0[a]
Wearing apparel., fur	16.7[a]	11.5[b]	12.2[a]
Wood and wood products	8.5[a]	5.7[a]	6.5[a]
Pulp, paper and paper products	-0.4	-0.4	-0.2
Publishing, printing, reproduction	3.9[a]	0.2	4.3[a]
Chemicals and chemical products	-6.8	-3.5[a]	-6.0[a]
Rubber and plastic products	7.4[a]	5.2[a]	6.7[a]
Other non-metallic mineral products	3.7[c]	2.7	3.7[c]
Basic metals	15.1[a]	10.6[a]	6.9[b]
Fabricated metal products	1.1	-2.0[b]	0.0
Machinery and equipment n.e.c.	12.4[a]	7.6[a]	9.3[a]
Electrical machinery and apparatus	12.6[a]	6.5[a]	9.4[a]
Instruments, watches and clocks	13.2[a]	5.2[b]	4.3[c]
Motor vehicles, trailers, semi-tr.	7.1[b]	6.7[b]	6.9[b]
Other transport equipment	11.8[a]	5.4[a]	6.6[a]
Furniture, manufacturing n.e.c.	13.8[a]	8.8[a]	11.5[a]
Recycling	20.3[a]	12.7[b]	15.6[a]

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 5: Labor productivity in 1997 by firm status

	Simple average	Weighted average
Continuing firms	6.201	6.264
Exiting firms	6.009	6.009
All firms	6.163	6.213

Notes: NOK 1000, in logs. Continuing firms: Present in 1997 and 2002.
Exiting firms: Present in 1997 but not in 2002.
Weighted average use firm size, in terms of employment, as weights.

Table 6: Worker characteristics by firm and worker status in 1997

	# Workers	Education[3]	Experience[3]
In continuing firms[1]	149186	11.07	19.26
In exiting firms	51085	11.14	18.48
- Switching to continuing[2]	18,997	11.26	19.02

Notes: [1]Continuing firms: Present in 1997 and 2002.
[2]Exiting firms: Present in 1997 but not in 2002.
[3]Unweighted mean of years of education and years of experience for workers in given category.

Table 7: Productivity effect of worker reallocation

	Scenarios[1]		
	Education & Experience	Experience	Education
Weighted productivity gain[2] (%)	-0.02	-0.04	0.02
Unweighted productivity gain (%)	-0.13	-0.17	0.04

Notes: [1]In the experience (education) scenario, we only consider the experience (education) of switching workers when recomputing Q, keeping education (experience) at its 1997 levels.
Under scenario "education-experience", we account for both education and experience of switching workers.
[2]We weight labor productivity using firms' employment.

Table 8: 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 9: 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 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.

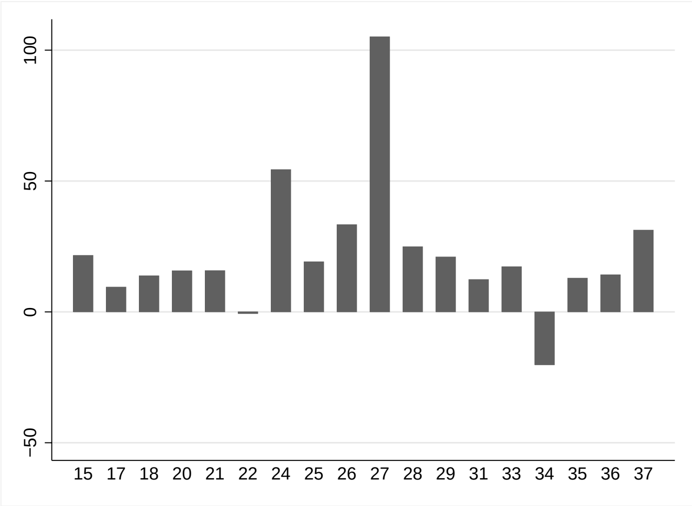

Figure 1: Job tenure. Difference between exporters and non-exporters in %, by industry.

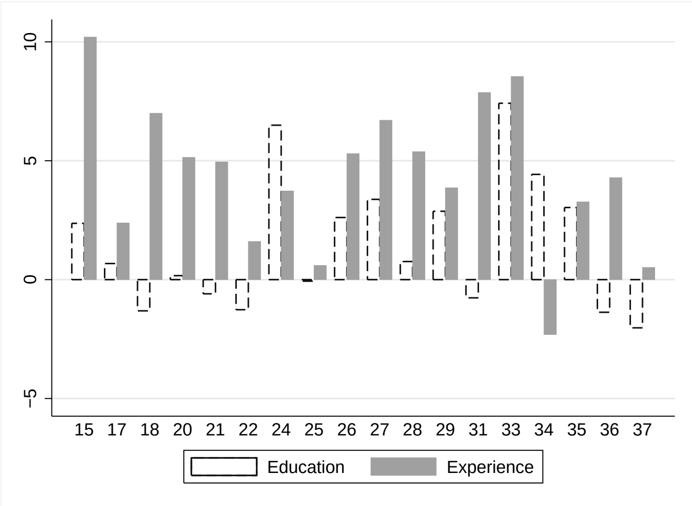

Figure 2: Labor market experience and education. Difference between exporters and non-exporters in %, by industry.

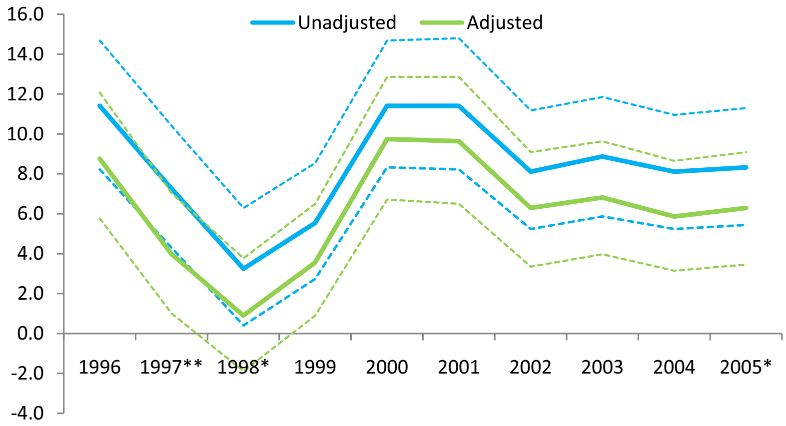

Figure 3: The TFP premium in %. Adjusted (Griliches method) and unadjusted. Dotted lines = 95% confidence intervals.

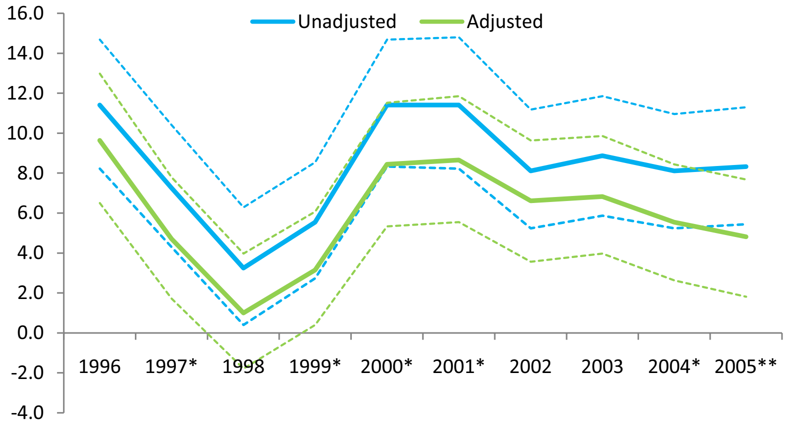

Figure 4: The TFP premium in %. Adjusted (Mincer method) and unadjusted. Dotted lines = 95% confidence intervals.

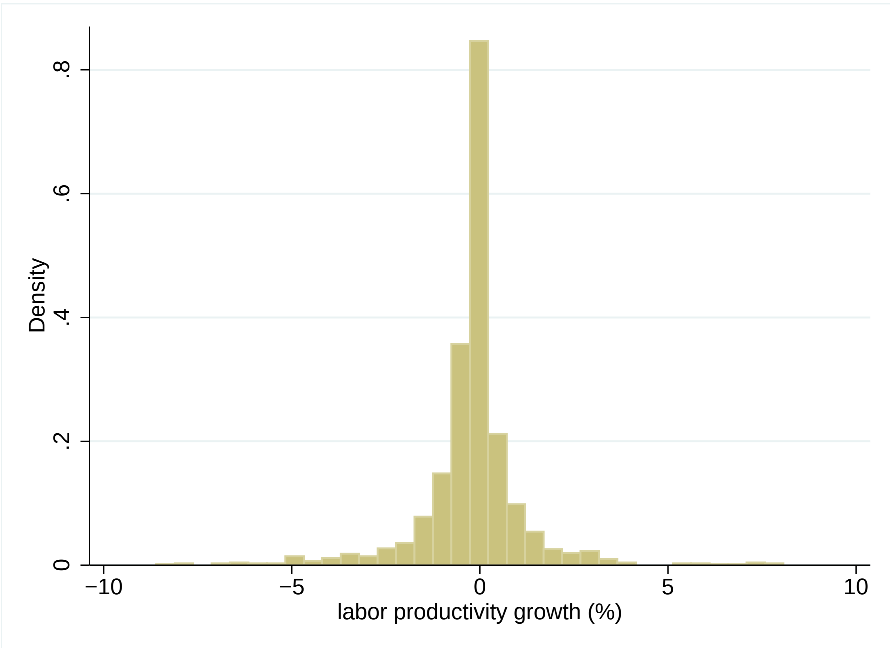

Figure 5: Labor productivity growth for firms receiving workers