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ABSTRACT

The Impact of Training on Productivity and Wages: Firm Level Evidence*

This paper uses firm level panel data of firm provided training to estimate its impact on productivity and wages. To this end the strategy proposed by Ackerberg, Caves and Frazer (2006) for estimating production functions to control for the endogeneity of input factors and training is applied. The productivity premium for a trained worker is estimated at 23%, while the wage premium of training is estimated at 12%. Our results give support to recent theories that explain work related training by imperfect competition in the labor market.

JEL Classification: J24, J31, L22

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1 Introduction

In recent years trade unions, employers and policy makers have emphasized the importance of skill upgrading of workers and life long learning in order to cope with increased pressures induced by technological change and globalization (e.g.; European Commission, 2007). While there exists a large literature showing that the accumulation of human capital through the general education system plays a crucial role in explaining long run income differences between rich and poor countries, much less work exists on the effects of training provided by firms, often requiring specific skills from their workers.

In his seminal work, Becker(1964) made a distinction between firm specific and general training. General training results in skills that are equally applicable at other firms while skills acquired through firm specific training are lost when the trained worker leaves the firm that provided training. Under perfect competition in the labor market, workers should pay for costs of general training and recoup these costs by earning higher wagers. When training is specific, firms pay (part of) the training costs[1]. However, Acemoglu and Pischke (1998, 1999a, 1999b) point out that in numerous cases firms provide and pay for training that is general in nature. They show how this can be explained by labor market imperfections. In particular, a necessary condition for firms to pay for general training is that wages increase less steeply in training than productivity. This is referred to as a compressed wage structure which can be caused by frictions in the labor market such as search costs, informational asymmetries, efficiency wages and labor market institutions such as unions or the presence of minimum wage laws. With a compressed wage structure, training increases the marginal product of labor more than wages, which creates incentives for the firm to invest in training.

While there exists substantial evidence that general education increases wages[2] and productivity of workers, there is hardly any work that studies the impact of work related training on firm level productivity and wages. Moretti

[1] In fact, with firm specific training it is more efficient if firms and workers share the costs and benefits of training. Wages of workers increase after specific training above the level they could earn elsewhere but lower than their marginal product which reduces both the probability they quit the firm and the propability they are laid off.

[2] Card (1999), for instance, summarizes various studies and concludes that the impact of a year of schooling on wages is about 10%.

(2004) focuses on plant level productivity gains from education, but he has no data on firm provided training. He finds that plants operating in cities that experience a large increase in the share of college graduates have higher productivity gains than in cities that have a lower increase in college graduates, but these productivity gains are offset by wage increases. Bartel (1995) studies how firm provided training affects wage profiles of workers and job performance scores in one large firm and finds that training has a positive effect. Dearden, Reed and Van Reenen (2006) analyze the link between training, wages and productivity at the sector level using a panel of British industries. They find that raising the proportion of workers in an industry who receive training by one percentage point increases value added per worker in the industry by 0.6% and average wages by 0.3%.

Our paper makes several contributions to the literature. First, we make use of firm level data on training. Belgian firms are obliged by law to submit a supplement to their annual income statement which contains information on various elements of training, such as the proportion of workers that received training, the number of hours they were trained and the cost of training to the firm. This data allows us to measure the impact of training on both wages and productivity at the firm level and we can infer whether trained workers are paid the value of their marginal product. By focusing on firm level data we are able to avoid possible aggregation biases and hence capture the effects of training more precisely. Second, the analysis at the firm level allows us to control for the endogeneity of training. To this end we estimate the production function using an estimation strategy recently introduced by Ackerberg, Caves and Frazer (2006) which allows us to control for the endogeneity of input factors. In addition, the production function estimates provide us with a measure of unobserved worker ability which we include in the wage equation to retrieve a consistent estimate for the impact of training on wages. Third, we are able to explore various dimensions of the data set. Because of the large number of observations, we can analyze differences between narrowly defined sectors with respect to the impact of training on firm performance and relate the incidence of training with quit and dismissal rates.

Our main findings can be summarized as follows. Training has a positive impact on productivity and wages. The marginal product of a trained worker is on average 23% higher than that of an untrained worker while wages only increase with 12% in response to training and the difference is statistically significant[3]. This finding is consistent with recent theories that explain firm provided training by models with imperfect competition in the labor market and is robust against different kinds of specifications and estimation strategies. Among the different manufacturing sectors, largest productivity gains can be found in the Chemicals and Rubber & Plastic industries. Finally we provide some indicative evidence that the observed training is general in nature.

The next section gives the empirical framework we use and we describe our estimation strategy in Section 3. We give an overview of the dataset in Section 4. Results are reported in Section 5 and Section 6 makes a distinction between firm specific and general training. Finally, we conclude in Section 7.

2 Empirical Framework

We infer the impact of training on both wages and productivity by applying a framework used by Hellerstein et al. (1999). The idea is to estimate both a wage equation and a production function to compare gains in wages with the gains in productivity that may arise in response to training. In competitive labor markets, returns from human capital formation accrue to workers in the form of wages and the productivity premium of a trained worker equals its wage premium[4]. While most studies that estimate wage differentials between different types of workers rely on individual level data, this option is not available to estimate productivity differentials since it is hard if not impossible to find individual level output data. Consequently we will rely on rich firm level data with information on the different kinds of characteristics of the workforce such as the amount of training among others. The drawback is that we can only estimate an average productivity and wage premium for trained workers and can not capture heterogeneity in these premia across different workers.

[3] These productivity and wage premia drop to 17% and 11% respectively when controlling for worker heterogeneity.

[4] The framework has been applied among others by Jones (2001) to examine the impact of education on earnings and productivity and by Hellerstein and Neumark (1999) to estimate whether the wage gap between men and women can be explained by productivity differentials. Frazer (2001) uses the methodology to find unbiased estimates for the impact of education on wages. More recently Van Biesebroeck (2007) applies the framework to estimate returns to human capital, including training, on both productivity and wages for some African countries and Dearden et al. (2006) estimate the impact of training on wages and productivity for a panel of UK industries.

2.1 Impact of training on productivity

The output of a firm i in period t is a function of capital and a quality labor aggregate used by the firm in period t. As is common in the literature, we assume that this function takes the Cobb-Douglas form:

$$Y_{it} = A_{it}\widehat{L}_{it}^{\beta_l}K_{it}^{\beta_k} \tag{1}$$

with Y_{it} value added, $\widehat{L}_{it}$ the quality of labor aggregate and K_{it} is capital of firm i in period t. A_{it} represents Hicks neutral technical efficiency of the firm. Taking natural logarithms of all variables, the logarithm of output can be written as linear function of the logarithm of inputs[5]:

$$y_{it} = \beta_0 + \beta_l\widehat{l}_{it} + \beta_k k_{it} + \mu_{it} \tag{2}$$

The productivity term a_{it} is decomposed in a fixed component β_0 which is common to all firms and a component μ_{it} which represents firm and time specific deviations from the average productivity level. So far, the assumption of the homogeneity of labor has been maintained. Now we relax this assumption and take into account the amount of training that is provided by each firm to its employees. There are several ways to bring training into the model. First, we define training as a discrete characteristic, namely we divide the labor force into trained and untrained workers. Second, we take into account the intensity of training and use hours of training as a measure for differences between employees.

If we model training as a discrete characteristic, the labor aggregate $\widehat{L}$ can be written as the sum of the number of each type of worker multiplied with its marginal productivity level relative to that of an untrained worker[6]. The relative (marginal) productivity differential of a trained worker compared to an untrained worker, ϕ_T, is defined as $\phi_T \equiv \frac{\partial Y/\partial L_T - \partial Y/\partial L_U}{\partial Y/\partial L_U} \equiv \frac{MP_T - MP_U}{MP_U}$ where L_U and L_T represent respectively the number of untrained and trained workers. We can then write the labor aggregate $\widehat{L}$ as

$$\widehat{L} = L_U + (1 + \phi_T)L_T \tag{3}$$

[5] Throughout the rest of the paper, lower case letters represent variables expressed in logarithms.

[6] Firm and time subscripts are omitted for the rest of this section. When we turn to the estimation strategy in the next section, we will reintroduce the subscripts.

This functional form assumes that trained and untrained workers are perfect substitutes and a firm makes its training decisions solely based on productivity differences between employees and the cost of training. We can rewrite $\widehat{L}$ as:

$$\widehat{L} = L(1 + \phi_T \frac{L_T}{L}) \tag{4}$$

Here L represents the total number of employees and is by definition the sum of both trained and untrained workers. Consequently, $\frac{L_T}{L}$ is the fraction of trained workers in the labor force. Substituting Equation (4) in Equation (2) gives:

$$y = \beta_0 + \beta_l l + \beta_l \ln\left(1 + \phi_T \frac{L_T}{L}\right) + \beta_k k + \mu \tag{5}$$

or when $\phi_T \frac{L_T}{L}$ is small, this can be approximated by

$$y = \beta_0 + \beta_l l + \beta_l \phi_T \frac{L_T}{L} + \beta_k k + \mu \tag{6}$$

In principle we can infer the training premium from a linear regression of output on capital, labor and the share of trained workers in total employment. A positive coefficient on the share of trained workers indicates that the marginal product of a trained worker is higher compared to the marginal product of an untrained worker. The precise magnitude of the average productivity premium can be retrieved by dividing the training coefficient by the labor coefficient[7] β_l. In Appendix A we generalize the approach to include multiple characteristics of the workforce. Note that we discard any heterogeneity in the impact of training across workers and we implicitly assume all trained workers have a similar productivity increase. We will interpret our estimates for the productivity premium more as an average effect of training on productivity. Moreover, we assume there exists only a direct effect of training on the productivity of the trained worker himself. However, training may also increase productivity of untrained coworkers through spillover effects (Blundell et al. 1999). Unfortunately, it is difficult to identify these spillover effects without individual level data or stringent functional form assumptions[8]. Consequently we choose not to control for spillovers to other workers. Our point estimates should be interpreted with caution since these possible effects are attributed to the estimated productivity

[7] This is because the impact of an extra trained worker also depends on the importance of labor in the production function: $\frac{\partial \ln Y}{\partial L_T} = \phi_T \beta_l$.

[8] For example when the spillover effect is a linear function of the share of trained employees, one could infer the spillover coefficient from adding the share of trained employees squared in the labor aggregate.

premium. Note that both inputs and the number of trained workers are likely to be correlated with elements of the unobserved productivity μ of a firm which complicates the identification of the coefficients. We turn back to this issue in Section 3.

So far we have defined training as a discrete characteristic. Either a worker has received training over the period or he has not. However, this is a simplification since there exists considerable variation in the amount of training each worker received. For example, the firm specific average training hours per worker trained ranges from less than 1 hour to more than 300 hours. To take into account these variations in training intensity we include training as a continuous variable instead of a binary variable. Frazer (2001) shows how to derive the labor aggregate in a production function consistent with Mincer (1974) when the characteristic that differentiates the labor force is a continuous variable[9]. In our baseline model, workers differ only by the amount of training they received. A typical equation in the style of Mincer (1974) that explains the earnings of individual j as a function of the amount of training he obtained, looks like:

$$\ln(W_j) = \alpha_0 + \alpha_T T_j + \nu_j \tag{7}$$

which means that the average wage bill of a firm can be written as $\sum_j \exp(\alpha_0 + \alpha_T T_j + \nu_j)$. Here T_j represents the amount of training hours worker j has received. Frazer (2001) proves that if the firm is maximizing its profits, the labor term in the production function should have the same form as the wage bill, i.e. $\widehat{L} = \sum_j \exp(\beta_1 + \beta_T T_j)$ and the production function can be written as follows:

$$Y = A(\sum_j \exp(\beta_1 + \beta_T T_j))^{\beta_l} K^{\beta_k} \tag{8}$$

where β_T measures how the contribution of an individual worker j to the aggregate labor term varies with the amount of training he received ($\partial \ln(\widehat{L})/\partial T_j = \beta_T$). Taking natural logarithms, this can be rewritten as:

$$y = \beta_l \beta_1 + \beta_l \ln(\sum_j \exp(\beta_T T_j)) + \beta_k k + a \tag{9}$$

[9] To be precise, Frazer (2001) derives this result under the assumption of perfect competition in the labor market. Intuitively, if a firm is profit maximizing and acts as a price taker in the labor market, differences in wages should reflect differences in marginal products and the aggregate labor term in the production function should have exactly the same functional form as the wage equation. However, with for example labor market frictions, productivity premia do not necessarily equal wage premia and we have to assume that the functional form of the labor aggregate in the production function is the same as the functional form of the wage equation.

A first-order Taylor approximation of the labor term results in a loglinear equation that can be estimated (cf. Frazer, 2001). The logarithm of output is a function of the logarithm of the number of workers and capital and the average training hours of all workers in a particular firm:

$$y = \beta_0^* + \beta_l l + \beta_l \beta_T \overline{T} + \beta_k k + \mu \tag{10}$$

The coefficient on average training intensity β_T measures how the labor aggregate changes with training intensity. The impact of training on output depends also on the importance of labor in the production function β_l, i.e. $\partial y/\partial T = \beta_l \beta_T$, which represents the percentage changes in output in response to variations in average training intensity of the workforce.

2.2 Impact of training on wages

We derive wage equations similar to Equations (6) and (10). The wage equation will be more descriptive than the structural productivity equation. Again, we first build up the empirical framework defining training to be a discrete characteristic. Second, we take into account the variations in training intensity in terms of training hours across trained employees.

To measure wage differentials between trained and untrained employees, we apply firm-level wage equations as in Hellerstein et al. (1999). We define a wage equation in the style of Mincer (1974) for individual j:

$$W_j = W_U D_{j,U} + W_T D_{j,T}$$

where W_j is the wage of individual j. W_U and W_T are the average wages of an untrained and trained employee respectively and $D_{j,U}$ and $D_{j,T}$ represent a dummy equal to one if employee j is untrained or trained respectively. By summing over all employees at a firm, the total wage bill of a firm equals by definition the sum of the wages of trained and untrained employees multiplied by respectively the number of trained and untrained employees active in the firm. This expression can be rewritten as

$$\overline{W}L = W_U L_U + W_T L_T = W_U L + \lambda_T W_U L_T = W_U L(1 + \lambda_T \frac{L_T}{L}) \tag{11}$$

where $\lambda_T = \frac{W_T - W_U}{W_U}$ represents the relative wage premium for a trained employee compared to an untrained one. Dividing both sides by the number of employees and taking logs of Equation (11) one obtains

$$\begin{aligned} \overline{w} &= w_U + \ln\left(1 + \lambda_T \frac{L_T}{L}\right) \\ &\approx w_U + \lambda_T \frac{L_T}{L} \end{aligned} \tag{12}$$

Where the last step follows from the fact that $\ln(1+x)$ can be approximated by x if x is small. This equation at the firm level is consistent with the individual level Mincer (1974) wage equations. Under perfect competition in the labor market, wages do not vary systematically across firms and regressing the average wage on a constant and the share of trained employees will give a consistent estimate for the relative wage premium of trained employees. However, we will include the capital intensity and total factor productivity in the estimation equation in order to allow for imperfectly competitive labor markets and unobserved differences in labor quality which should be reflected in total factor productivity. Adding a vector of control variables X and an additive error term[10] to equation (12) we get:

$$w = w_U + \lambda_T \frac{L_T}{L} + X\gamma + \varepsilon \tag{13}$$

which can be estimated by applying a least squares estimator[11].When we find a positive association between the average wage at the firm and the share of trained workers this is an indication of a positive wage premium for trained workers. More precise, the coefficient on the share of trained workers will represent an average wage premium of a trained worker compared to an untrained worker[12].

The derivation of a firm level wage equation when we take into account variations in training intensity across trained workers is similar to the derivation of the labor aggregate in the production function of the previous section. The average wage in a firm can be written as:

$$\overline{w} = w_U + \alpha_T \overline{T} \tag{14}$$

[10] Note that Equation (12) is not a behavioral equation, but simply defines the average wage to be a function of the wages of each different type of worker. The error term that we add can represent measurement error, variation across firms in wages across firms unrelated to productivity differences, regional differences in labor market conditions, ...

[11] Again, we refer to Appendix A for the inclusion of multiple workforce characteristics in the wage equation.

[12] Similar to the derivation of the productivity premium, we have assumed the wage premium is constant and equal for all workers that receive training. This seems a quite harsh assumption and we interpret the coefficient on the share of trained workers more as an average impact of training on wages.

Where $\overline{T}$ represents average training costs per employee, α_T measures how wage premiums change with the intensity of training ($\partial w/\partial T$) and w_U is the average wage of a worker that received no training at all. Again we add an additive error term and control variables:

$$\overline{w} = w_U + \alpha_T \overline{T} + X\gamma + \varepsilon \tag{15}$$

which can be estimated using ordinary least squares.

3 Estimation strategy

One needs to be careful in estimating the production function in Equation (6) since inputs are likely to be correlated with the unobserved productivity term. In this section, we describe in detail how we solve this problem. Recall the production function derived in the previous section:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_l \phi_T \frac{L_{T,it}}{L_{it}} + \beta_k k_{it} + \omega_{it} + \eta_{it} \tag{16}$$

where the unobserved productivity term μ_{it} is divided into two components, namely ω_{it} and η_{it}. Unobservables that are not seen by the firm at the moment when it makes its input decisions are represented by the mean zero error term η_{it}. Consequently, inputs will be uncorrelated with this unobservable. An example is an unexpected machine breakdown or strike. Also measurement error in the output variable can be incorporated in η_{it}. The ω_{it} represents productivity unobserved by the econometrician, but observed by the firm before making its input decisions. Examples include managerial ability, expected machine breakdowns, technological progress, worker ability,... As such the input choices are likely to be correlated with the unobserved error term ω_{it} and estimating Equation (16) with OLS will generate biased point estimates. This simultaneity bias has been documented first by Marschak and Andrews (1944)[13]. Note that also the unobserved (by the econometrician) ability of employees or labor quality is likely to be included in the productivity term ω_{it}. If firms tend to provide training to the most able employees, for example because they are faster learners and therefore require a smaller training investment, the estimated coefficient on the training variable will be upward biased.

[13] For an overview of the outstanding issues in estimating production functions, we refer to Ackerberg et al. (2005).

Olley and Pakes (1996) offer a solution to the endogeneity problem. They set up a dynamic model and derive the productivity ω_{it} to be a function of investment and capital. As such, productivity can be proxied by a nonparametric function of investment and capital and can be controlled for in the estimation of Equation (16). The drawback of this method is that only observations with positive investment levels can be used in the estimation. Levinsohn and Petrin (2003) overcome this problem by using material inputs instead of investment in the estimation of productivity ω_{it}. Both methods assume that labor has no dynamic implications and hence the choice of labor in year t has no impact on future profits. This implies among others that there can be no hiring and firing costs and that firms can choose each period the optimal amount of labor at a given wage rate without any limitations. Given that Belgium is a highly unionized country with rigid labor markets and that there exist considerable costs in laying off employees, we will relax this assumption. Moreover, Ackerberg, Caves and Frazer (2006) note that identifying the coefficients on labor and materials using the Levinsohn and Petrin (2003) or Olley and Pakes (1996) methodology could be problematic due to collinearity issues. For these reasons, we will follow the methodology proposed by Ackerberg, Caves and Frazer (2006) to correct for the simultaneity bias, which we will discuss now in more detail.

We keep the timing assumption made in Levinsohn and Petrin (2003) and Olley and Pakes (1996) about the capital accumulation function:

$$k_{it} = (1 - \delta)k_{it-1} + i_{it-1} \tag{17}$$

with i_{it-1} investment decided in period $t-1$ which only enters the capital stock in year t. Intuitively, the expression means that it takes a full period to order and install the new capital goods before they enter the production process. We will use this assumption to identify the capital coefficient in the second stage of the estimation strategy since by definition the capital stock will be uncorrelated with the part of productivity in year t, unforeseen in year $t - 1$. Furthermore we assume that ω_{it} follows a first-order Markov process:

$$p(\omega_{it}|I_{it-1}) = p(\omega_{it}|\omega_{it-1}) \tag{18}$$

where I_{it} is the information set of firm i at period $t - 1$. This assumption means that firms' expectations of future productivity only depend on current productivity. We assume material input to be chosen after labor input and training which seems plausible for an economy with rigid labor markets like

Belgium. As a result, material demand will not only be a function of capital and productivity (as in Levinsohn and Petrin 2003), but also of labor and training:

$$m_{it} = f_t\left(\omega_{it}, l_{it}, \frac{L_{T,it}}{L_{it}}, k_{it}\right) \tag{19}$$

When this material demand function is strictly increasing in productivity ω_{it}, it can be inverted to obtain an expression for productivity[14] $\omega_{it} = f_t^{-1}\left(m_{it}, l_{it}, \frac{L_{T,it}}{L_{it}}, k_{it}\right)$. Note that we have to assume that productivity is the only unobservable in the material demand function. This means that input prices are constant across firms[15] and there are no other unobservables affecting material demand but not production. An important advantage of this procedure is that the setting allows labor and training to have dynamic implications such that the optimal choice of training, l_{it} and k_{it} depend on previous labor, training and capital input decisions[16]. Obviously, the optimal choice of material input does not depend on previous choices of capital, labor and training. Material input in period t has only an impact on profits in period t and thus depends only on the other inputs in year t. Substituting inverse material demand in the production function gives the first stage equation[17]:

$$y_{it} = \beta_l l_{it} + \beta_{tr}\frac{L_{T,it}}{L_{it}} + \beta_k k_{it} + f_t^{-1}\left(m_{it}, l_{it}, \frac{L_{T,it}}{L_{it}}, k_{it}\right) + \eta_{it} \tag{20}$$

We will use a series estimator with a polynomial in materials, labor, capital and training to proxy the inverse material input function $f^{-1}(.)$. Clearly β_l, β_k, and β_{tr} will not be identified here since these inputs are also included in the inverse material demand function. This is in contrast with Olley and Pakes (1996) and Levinsohn and Petrin (2003) who identify the labor coefficient in

[14] The monotonicity condition states that conditional on capital and labor (both untrained and trained) , intermediate input use has to increase in productivity. If a higher productivity leads to a higher value of the marginal product of materials, firms in a competitive environment will use generally more materials to produce a higher output up to the point where the value of the marginal product of materials equals the price of materials again. In Appendix B we show some more formal conditions for the monotonicity assumption to hold.

[15] We include year dummies to control for input prices changing over time.

[16] As noted by Ackerberg, Caves and Frazer (2006), another advantage of this procedure is that it is consistent with other unobservables affecting firm's choices of l_{it}, k_{it} and L_{iT}. This is because m_{it} depends directly on l_{it}, k_{it} and L_{iT}. These unobservables, such as dynamic adjustment costs, both linear as non-linear, are allowed to be correlated over time since material inputs are only relevant for current output. However, there cannot exist unobservables that directly affect material demand since they would make the inversion of the material demand function invalid.

[17] β_{tr} is defined as $\beta_{tr} \equiv \beta_l \phi_T$

the first stage of the estimation strategy. Here, the first stage only serves to separate η_{it} from ω_{it}. Estimating the above equation gives a measure $\widehat{\Phi}_{it}$ for the following term:

$$\Phi_{it} = \beta_l l_{it} + \beta_{tr} \frac{L_{T,it}}{L_{it}} + \beta_k k_{it} + \omega_{it} \tag{21}$$

which is in fact output net of the error term η_{it}. The estimate $\widehat{\Phi}_{it}$ will be used to identify the input coefficients in the second stage. Since productivity ω_{it} is assumed to follow a first-order Markov process, it can be written as follows:

$$\begin{aligned} \omega_{it} &= E\left[\omega_{it} | I_{it-1}\right] + \xi_{it} \\ &= E\left[\omega_{it} | \omega_{it-1}\right] + \xi_{it} \\ &= g(\omega_{it-1}) + \xi_{it} \end{aligned} \tag{22}$$

where ξ_{it} represents the innovation in productivity, namely the part of productivity in period t that was unforeseen by the firm in period $t-1$. Given the timing assumption that the capital stock in period t was decided in period $t-1$, this leads to a first moment condition which will allow us to identify the capital coefficient:

$$E\left[\xi_{it} | k_{it}\right] = 0 \tag{23}$$

Moreover, we assume that labor input and the amount of training do not depend on the innovation in productivity. For the labor coefficient, this is a more strict assumption than usually applied. However, in the Belgian context there are substantial labor adjustment costs such that labor is not freely variable input[18]. Concerning the training variable, several human resources managers confirmed that the amount of training provided to workers is mostly decided one year in advance when making up the budget for the following year, which makes the amount of training independent from the innovation in productivity, ξ_{it}. Consequently, the moment conditions to identify the labor and training coefficients in the second stage are[19]:

[18] For example, the OECD Employment Protection Legislation for Belgium is among the highest among the industrialized countries (higher scores indicate stricter regulation). Belgium has especially a high score for the notice and severence pay for individual dismissals, legislation concerning collective dismissals and temporary employment (OECD 2007).

[19] These timing assumptions are relaxed in the robustness checks. Namely we will allow training and part of the labor stock to be correlated with the innovation in productivity.

$$E\left[\xi_{it}| \begin{array}{c} k_{it} \\ l_{it} \\ L_{T,it}/L_{it} \end{array}\right] = 0 \tag{24}$$

In practice, we apply the first stage by non-parametrically regressing y_{it} on the production inputs. This gives us an estimate $\widehat{\Phi}_{it}$ for $\Phi_{it} = \beta_l l_{it} + \beta_{tr}\frac{L_{T,it}}{L_{it}} + \beta_k k_{it} + \omega_{it}$. Given a candidate value for the vector of input coefficients $(\beta_l, \beta_k, \beta_{tr})$, we can compute $\widehat{\omega}_{it}$ as follows:

$$\widehat{\omega}_{it} = \widehat{\Phi}_{it} - \beta_l l_{it} - \beta_{tr}\frac{L_{T,it}}{L_{it}} - \beta_k k_{it} \tag{25}$$

Next, we non-parametrically regress ω_{it} on ω_{it-1}. The residuals from this regression $\widehat{\xi}_{it}$ represent innovations in productivity, which are by assumption uncorrelated with training, labor and capital. This renders the above moment conditions and their sample analogue:

$$\frac{1}{T}\frac{1}{N}\sum_t \sum_t \widehat{\xi}_{it} \begin{pmatrix} k_{it} \\ l_{it} \\ L_{T,it}/L_{it} \end{pmatrix} \tag{26}$$

and we compute the sample analogue for each $(\beta_l, \beta_k, \beta_{tr})$ For each new candidate value of $(\beta_l, \beta_k, \beta_{tr})$, we obtain new estimates for ξ_{it} and we repeat this procedure until Equation (26) is minimized.

Given the input coefficients we found in the previous step, we find an estimate for total factor productivity by applying Equation (25). We use this estimate in the wage equation as control variable to pick up unobservables such as worker ability that influence wages of the workers[20]. When not controlled for, these variables could cause our estimate for the wage premium to be biased since for example more able workers are also more likely to receive training. Standard errors for all coefficients are obtained by using a bootstrap procedure with 500 replications. We apply a block bootstrap procedure such that the error term is allowed to be heteroskedastic and correlated over time t, for a given firm i but is assumed to be independent over i.

[20] This is a similar strategy as applied in Frazer (2001).

4 Data Description

Data is obtained from the Belfirst database. This database commercialized by Bureau Van Dijck includes information about all Belgian firms that need to file annually an income statement.[21] We obtained an unbalanced panel for the period 1997-2006 of both manufacturing and non-manufacturing firms. We select a number of key variables needed for estimation of the production function and wage equation such as value added, number of employees (in full time equivalents), labor costs, material costs and the capital stock. For manufacturing sectors, these variables are deflated using price deflators at the 4 digit NACE level from the European Statistical Office[22]. For the non-manufacturing sectors we use a NACE 2 digit price deflator from the EU Klems database. In addition to the aforementioned variables, Belgian firms are obliged to report information about formal training[23] they provide to their employees. In particular, they have to report the number of employees that followed some kind of formal training as well as the hours spent on this training and the training costs. This allows us to obtain a firm-level measure of training for more than 170, 000 Belgian firms active in manufacturing and non-manufacturing sectors.

Table 1 provides some summary statistics of the dataset used. A Belgian firm active in the private sector employs on average 16.9 employees and generates a turnover of around 10 million euro. It pays an average wage of around 35, 000 euro and the average labor productivity (= value added per employee) equals 63, 900 euro. The second and third column compare these figures between firms that provided training to at least one employee in at least one year of the sample period with firms that have never trained an employee over the sample period. By comparing columns (2) and (3) it can be seen that less than 10% of the firms have ever invested in training of one of their employees. These firms are typically larger in terms of both employment and turnover. Moreover they pay higher wages and have a higher labor productivity. Surprisingly, firms that provide training to their employees have a lower capital/labor ratio than non-training firms, but this result changes when we control for other characteristics as we will see below. In firms that train their workers in a given period, more than

[21] These are all Belgian enterprises with the exclusion of one-man businesses.

[22] For some 4 digit NACE sectors, price deflators are not reported. Here we use the 3 digit deflator.

[23] Formal training excludes training that takes place at the workfloor or self study. The training has to take place at a seperate training room or workfloor especially developed for training activities. Training can take place inside or outside the firm.

50% of the employees benefit from this training and spent on average almost 40 hours on this training. The average cost of training an employee equals more than 1,500 euro.

Table 2 shows the results of the regression of different key variables on a training dummy. This dummy equals 1 when a particular firm provides training to at least one of its employees in a given period and 0 otherwise. The dependent variable is expressed in logarithms, such that the coefficient on the training dummy can be interpreted as a percentage difference[24]. The first column of Table 2 shows the results of this exercise. A training firm is more than twice as large as a non-training firm and pays gross wages that are 36% higher. Labor productivity is also higher but the difference is smaller than for labor costs. In column (2), we control for the size of the firm, that is we include the number of employees as explanatory variable and in column (3), we also include NACE 4 digit dummies to control for sector characteristics. Now, labor productivity in training firms is 27% higher than in non-training firms while labor costs are only 18% higher. Note that when controlling for industry characteristics and the size of the firm, training firms have a higher capital-labor ratio than non-training firms.

There exists considerable variation in the amount of training across sectors. This is illustrated in Table 3 where the percentage of firms that provided training to their employees in 2006 is shown. We also show the percentage of workers that received some kind of (formal) training and the share of training costs in total labor costs. These two measures are weighted averages, that is the total share of trained workers in sector j equals $\frac{\sum_i L_{T,ij}}{\sum_i L_{ij}}$, where i is a firm indicator. Likewise, the share of training costs in total labor costs is the fraction of total training costs in sector j divided by total labor costs in the sector. Despite that only slightly more than 5% of the firms provided training to at least one employee in 2006, more than 30% of all employees received training. This is because training firms are much larger than non-training firms as can be seen in Table 1. Training costs make up almost 1% of total labor costs. In general, manufacturing firms train more than their non-manufacturing counterparts. The most training intensive sectors include Manufacturing of Chemical Products, Telecommunications and Electricity Sector. Least training can be found in sectors such as Agriculture, Construction and Hotels & Restaurants.

[24] Of course this is an approximation, certainly because for some variables, the difference between training and non-training firms is quite large.

5 Results

This section presents the results of the empirical analysis. First, we estimate productivity and wage premia for all sectors pooled together and for each sector separately. Next we measure training as a continuous variable before moving to some robustness checks. Finally we include other sources of worker heterogeneity in the analysis, under the assumption of both perfect and imperfect substitution between different types of workers.

5.1 General Results

Table 4 shows the results of estimating Equation (6) for all firms active in all sectors pooled together and for manufacturing and non-manufacturing separately[25]. The first column for each subsample (Total, Manufacturing and Non-Manufacturing) reports the estimation results for the full sample by applying ordinary least squares (OLS1)[26]. Unfortunately, many firms do not report material costs[27] such that the estimation methodology described in Section 3 can only be applied to a subset of firms. To allow comparison between the ordinary least squares estimates and the estimates controlling for the endogeneity of inputs in the third column(ACF), we report in the second column results for least squares estimation (OLS2) on this subset of firms[28]. The estimates reported in column (1) show that training has a strongly significant and economically important effect on productivity. These coefficients imply that raising the share of trained workers by 10% points, will increase value added by 4.6%. In column (2), OLS estimates for the subset of firms that report material costs are displayed. The coefficient on training drops somewhat to .300 but remains highly significant, both statistically as economically. A possible explanation for the coefficient to drop is that a disproportionate number of small firms are excluded from the sample as they are not required to report material costs. It is generally accepted that larger firms are more productive and as seen in Table 1, larger firms are more likely to train their employees. This positive correlation can bias

[25] Manufacturing firms are firms active in NACE sectors 15 to 36. The other sectors are pooled together as non-manufacturing sectors.

[26] All regressions include year and industry dummies. Industry dummies are at the NACE 2 digit level for estimations on the whole sample and at the NACE 4 digit level for regressions at the sector level.

[27] Only large firms in Belgium have to submit a full version of the annual report. Smaller firms only have to submit a shorter version which does not include material costs. Firms are defined to be large if they have on average more than 50 employees, realize a turnover of more than 7.3 million euro or report a total value of assets of more than 3.65 million euro.

[28] All standard errors are robust to heteroskedasticity and within group correlation.

upward the training coefficient in column (1).

Controlling for the endogeneity of inputs (and training) causes the training coefficient to drop to .24 as shown in column (3). The estimates imply that value added increases by 2.4% in response to an increase of 10% points of the share of trained workers such that even after controlling for the possible endogeneity of training, there remains a substantially large impact of training on productivity. Note that the results imply that on average the marginal product of a trained worker is around 32% (= .243/.764) higher than the marginal product of an untrained worker. Again, one has to bear in mind that this is an estimate for the average effect of training on the marginal product of workers. Moreover, when there exist spillover effects to untrained workers, our measure includes these effects and the direct impact of training will be lower. The results for Manufacturing industries and Non-Manufacturing separately are comparable, although we find a slightly stronger impact of training in non-manufacturing sectors.

In Table 5 results for the estimation of the wage equation (13) are reported. Again the exercise is done for the whole sample and the manufacturing sector and the non-manufacturing sector separately. For each different sample, three different specifications are estimated. First, log wage is regressed on the share of trained workers together with year and sector dummies (OLS1). Second, this exercise is repeated, but the sample is now restricted to firms included in the productivity estimation sample where we control for the endogeneity of inputs. As a result, the coefficient on training drops from .438 to .200 and a similar reasoning as with the productivity analysis can be applied. In the third specification, we add controls in the wage equation. In particular, we add the capital-labor ratio and total factor productivity as control variables. For total factor productivity, we use our estimate for ω_{it} from the productivity equation and includes among others the ability of the labor force. By including total factor productivity in the wage equation we control for these factors that could be correlated with the amount of training in each firm. We find that in the total Belgian private sector, wages of trained employees are 16.7% higher than wages of untrained employees[29].

[29] Note that the training variable measures the training flow, namely the number of workers trained in a given year. If the subsample of workers receives training is the same every period, this will lead the amount of training per trained worker to be underestimated. If the workers that receive training are different every year, this will lead our estimate for the number of trained workers to be underestimated. We used the perpetual inventory method to construct

Results in Table 4 and Table 5, show that the impact of training on wages is smaller than the impact on productivity[30]. The productivity premium for a trained worker is almost twice as high as his wage premium. We can statistically test the equality of ϕ_T and λ_T. Performing a Wald Test of this non-linear hypothesis (delta method) [31] results in a Chi-square value of 128.2 which means that the null of equal coefficients can be rejected at any conventional significance level. The same is true for the manufacturing sector and non-manufacturing sector separately with Chi-square values of 14.1 and 113.0 respectively. The fact that we find the impact of training on productivity to be higher than the impact on wages, gives support to the Acemoglu and Pischke (1999a) model that explains why firms invest in the general training of their employees. A necessary condition is that productivity of employees increases more than their wages in response to training[32]. An important consequence is that in contrast to Becker (1964), it is possible that there is underinvestment in training.

5.2 Results Sector Heterogeneity

So far, the assumption of equal production technologies in all Belgian sectors has been maintained. Clearly this assumption is too strong, especially when pooling manufacturing and non-manufacturing sectors together. In Tables 6 and 7 we estimate the impact of training on productivity for each NACE 2 digit sector separately. The unweighted average for the training coefficient over all manufacturing sectors equals .231 when we estimate Equation (6) by ordinary least squares. Controlling for the possible endogeneity of training, we find that

a measure for the stock of trained workers and experimented with different depreciation rates, both dependent and independent of the number of workers that leave the firm. Our main results are robust to the use of the stock or flow of trained workers. These results are not reported for brevity.

[30] We compare the first column of the wage equation with the first column of the production function, since in both specifications, we do not control for the possible endogeneity of training. Both coefficients will likely to be upward biased (for example more able workers are more likely to receive training and more able workers generate higher output and receive higher wages). The same reasoning explains why we compare the second and third specification of the wage equation with the second and third specification of the production function respectively. In the third specification, we control for the endogeneity of training in both the production function as in the wage equation.

[31] Again, to receive an estimate for ϕ_T, we divide the coefficient on the share of trained workers reported in Table 4, by the labor coefficient. Consequently, the null is: $(\beta_{tr}/\beta_l) - \lambda_T = 0$, where $\beta_{tr} = \phi_T \beta_l$. This hypothesis can be tested by applying the Delta method.

[32] Note that Becker (1964) also allows for the possibility that firms pays (part of) the training costs. For this to be the case, the training needs to be firm specific in nature. We will turn back to this issue in the last subsection.

the average training coefficient drops to .177. The average labor coefficient decreases from .763 to .741 which indicates that our estimation procedure does a good deal in controlling for a likely upward bias on the labor and training coefficients. The results imply the marginal product of a trained worker is about 23% higher than that of an untrained worker. Focusing on the manufacturing industries, we find that for 14 out of 17 sectors, the training coefficient goes down compared to the least squares estimates. Largest productivity gains from training can be found in the Chemicals sector and Rubber and Plastic Sector[33]. Also the labor coefficient goes down in most sectors. Note that the sectors for which the labor coefficient increases, are sectors for which this coefficient is estimated relatively imprecise[34]. The results for the non-manufacturing sectors are less satisfactory, which is not surprising given the problems with estimating production functions for non-manufacturing sectors. However, we do find positive and significant effects of training on worker productivity and for the majority of sectors, the training coefficient goes down when controlling for the possible endogeneity of inputs. The unweighted average of the training coefficient over all non-manufacturing sectors drops from 0.23 to 0.19 when moving from OLS to the adjusted Ackerberg et al. (2006) methodology. Again we find that productivity gains from training are slightly larger in the non-manufacturing sectors compared to manufacturing sectors.

In Tables 8 and 9, we report results from estimating the wage equation for each NACE 2 digit sector separately. In both tables, we only report the coefficient on the share of trained workers for expositional reasons. Again, the aforementioned three specifications are reported. The number of observations refers to those used in the first specification, the number of observations used in the second and third specification are the same as in the productivity tables. Similar to the results of all sectors pooled together, the training coefficient drops when moving from the full sample to the restricted sample (with only firms that report material costs). Also inserting control variables in the wage equation lowers the training coefficient. The unweighted average of the training coefficient in this specification equals 0.122, which means that on average a trained employee earns 12% more than its untrained counterpart. For the manufacturing and non-manufacturing sectors separate, this average equals .142 and .100

[33] There are alse large gains in the sector of Wood Products, but here the training and labor coefficient are estimated imprecise.

[34] For example the standard errors for the sectors Wearing Apparel, Wood Products and Rubber and Plastic are considerably higher than those of other sectors.

respectively.

Comparing the impact of job related training with the impact of general education on wages, one finds these similar in magnitude. In his survey, Card (1999) reports estimates for the impact of one year of education on wages between 5 and 15% while we estimate the wage premium for trained employees to be 12%. However, note that the average training duration is only around 2 weeks, implying much larger returns to a week of training compared to a week of schooling. A possible explanation could be that work related training is much more designed to increase productivity directly than general education. While large parts of the general education system are devoted to increasing general knowledge not directly applicable in a professional career, one would not expect this to be the case for firm induced training. Note that our estimates for the impact of training on productivity and wages are considerably smaller that those obtained by Dearden et al. (2006) for UK manufacturing firms[35]. They observe training at the sectoral level instead of at the firm level and so their measure includes possible spillovers of training from workers who switch from one employer to another[36].

Figure 1 combines the estimates of the impact on training and productivity. The 45° line is plotted, such that all observations above this line represent sectors for which the impact of training on productivity is larger than the impact of training on wages[37]. Most of the sectors are located above this line which is consistent with Acemoglu and Pischke[38] (1999a). The correlation between the productivity and wage premium equals .64 and is highly significant.

[35] They find that raising the fraction of trained workers with 10%, increases value added by 6% and wages by 3%.

[36] However, this can only explain part of the difference since their estimate is almost three times as large as ours.

[37] We left out sectors 1-Agriculture, 64-Post and Telecommunications and 65-Financial Intermediation which reported all three a very large impact on productivity and a low or even zero impact on wages. Moreover, the number of observations used in the estimation was limited for these sectors.

[38] This finding on itself is also consistent with firm specific training and perfect competition in the labor market. An issue we will turn back to in the last section.

5.3 Training as a continuous variable

In Table 10 we redefine the training variable as average training hours per employee and estimate Equations (10) and (15) to determine the impact of training intensity on productivity and wages respectively. Again results are reported for the whole sample and manufacturing and non-manufacturing separate. We control for the possible endogeneity of training in both the production and wage equation, applying our estimation strategy described above. The coefficient on average training intensity in the production function equals .0041 implying that β_T equals .0053 which is considerably higher than our estimate for the impact of training intensity on wages (.0031). These figures imply that increasing the average training hours per employee with 10 hours, raises output by 4% or that a worker with the average amount of training (40 hours) is around 20% more productive than an untrained worker while wages are only around 12% higher. The difference between the wage and productivity premium is again highly significant. Also for the manufacturing and non-manufacturing sectors separately, the productivity premium is higher than the wage premium, although the difference is not statistically significant for the manufacturing industries[39]. A summary of the results for sector specific estimates are reported in the last columns and Figure 2 where the 45° line is added[40]. It can be seen that for the majority of sectors, investing in training has a larger impact on marginal productivity of a worker than on its wage. The correlation between the impact on productivity and on wages equals .57 and is highly significant.

5.4 Robustness Checks

We performed a number of robustness checks to show that results are not driven by one particular specification. First, we dropped the linear approximation of the training term in Equations 2 and 13. In the estimation strategy for the production function, we adjust the computation of the productivity estimates $\widehat{\omega}_{it} = \widehat{\Phi}_{it} - \beta_l l_{it} - \beta_l \ln(1 + \phi_{T,it} \frac{L_{T,it}}{L_{it}}) - \beta_k k_{it}$ and instead of applying linear techniques to estimate the wage equation we use non-linear least squares. A

[39] We also experimented with training costs as a measure for training intensity. The results showed that the impact of training on productivity was significantly higher than the impact of training on wages. A worker which received the average amount of training, measured by the training costs, was 20% more productive than an untrained worker while its wage was only 15% higher.

[40] Sectors 14-Other Mining and Quarrying, 21-Pulp and Paper Products, 37-Recycling and 64-Post and Telecommunications are left out.

summary of the results is reported in Table 11. Results are qualitatively and quantitatively similar to the linear approximation[41], although the magnitude of the training effect is estimated to be slightly higher. Again, the productivity premium exceeds the wage premium. Furthermore, we estimate Equations (2) and (13) with Zellner's seemingly unrelated regression (SUR) estimator, which allows the error terms of both equations to be correlated. Again the main results hold in that the productivity premium is higher than the wage premium for trained employees[42]. The difference is also statistically significant. Third, we add the average salary in a firm as control variable in the production function instead of applying the Ackerberg, Caves and Frazer (2006) estimation strategy. The average firm-level wage should pick up unobserved labor quality and productivity differences if workers are paid their marginal product. Also this strategy leaves our main conclusions unaffected. Finally, there could be concerns that training intensity does depend on the innovation in productivity. For example, in case of an unexpected economic downturn firms could send their employees more easily on training since the opportunity cost of training is lower which would create a downward bias in the estimated training coefficient. To control for this, we alter the moment conditions in Equation (24) and include training lagged one period instead of contemporaneous training as instrument. Results are reported in the last two rows of Table 11. Compared to Table 4, the estimated productivity premium drops somewhat but remains higher than the wage premium of trained workers.

5.5 Worker heterogeneity

There could be concerns that our methodology does not fully control for worker heterogeneity and our training coefficient is picking up differences in the marginal product between different types of workers unrelated to training. To control for this, we include in this subsection other forms of worker heterogeneity in the empirical framework. First, we include measures for the number of blue collar versus white collar workers and the schooling level of the workforce, but keep the assumption that these are perfect substitutes to each other. Second,

[41] Note that the reported coefficients are direct estimates for ϕ_T and should be compared with β_{tr}/β_l in Table 4.

[42] Here we do not control for the possible endogeneity of training in the production function. For the wage equation, we exclude the control variables. One can argue that the bias of the estimated training coefficient is more or less the same in both the wage equation and production function .

we allow for imperfect substitutability between different types of workers. The empirical framework to estimate the productivity and wage premia when the workforce can be divided among several dimensions is outlined in Appendix A.

Perfect Substitution between Different Types of Workers

Here, we include different forms of worker heterogeneity. We maintain however the assumption that different types of workers are perfect substitutes. First, we make a distinction between blue collar workers, white collar workers and managers. Second, we construct a measure for the education level of the worker and finally we include firm fixed effects which should pick up all other forms of labor force heterogeneity that are constant over time.

Besides the number of trained employees at each firm, we also observe the number of blue collar workers, the number of white collar workers and the number of managers active in a firm. We insert the share of blue collars, white collars and managers in the production function and wage equation (cf. Equations A.5 and A.10)[43] and apply again our methodology described above to control for the endogeneity of training. Again, this leads to conclusions comparable to those in our base specification. Results for sectors pooled together are reported in Table 12. The coefficient on training drops to .18 in the production function and to .09 in the wage equation. However, the impact of training remains statistically significant as well as the difference between the productivity premium and wage premium. The median of the training coefficient in the production function is .14 and .11 in the wage equation when estimating the model for each NACE 2 digit sector separately[44].

Moreover, we construct a measure for the average education level of the workers. Although we do not possess detailed information about the skill composition of workers, we observe the education level of every employee that leaves or enters the firm in a given year[45]. We only observe this information for a lim-

[43]For the whole sample, around 52% of the workforce is blue-collar, 44% white collar and 1.4% management. In the manufacturing sector the shares are respectively 66%, 31% and 1.6% and in the services sectors respectively 45%, 51% and 1.3%. The percentages do not sum up to 100% because some of the workers have an undefined contract and can not be classified.

[44]Dividing the training coefficient by the labor coefficient results in a median productivity premium of a trained worker of 17%.

[45]More precise we observe whether the highest education of an entrant or departure is primary, secundary, higher or university. We define an employee to be high-educated if he

ited sample of large firms[46]. Using this data, we compute the educational level of the inflow and outflow of employees and we take the average over all years to retrieve a proxy for the educational composition of each firm's workforce. We include the share of high-educated employees in both the production function and wage equation and estimate both equations controlling for the possible endogeneity of inputs (cf. Equations A.7 and A.11) . As can be seen from the last two rows of Table 12, the training coefficient drops somewhat compared to the base specification. However, the impact of training on productivity remains larger than the impact on wages. The results also indicate[47] that a schooled worker is almost two times as productive as an unschooled worker and earns a substantially higher wage but this wage premium is lower than the productivity premium, namely 70%.

Finally we repeated the exercise with firm fixed effects. These should pick up all unobserved worker heterogeneity that is constant over time. Unfortunately, using fixed effects to estimate production functions does not perform very well. When there is measurement error in the input variables, first or mean differencing can exacerbate the bias in the input coefficients estimates. This is especially true for highly persistent input variables (Griliches and Hausman 1986) such as capital and training. Results are reported in Appendix C. Table C.1 shows that for the production function, as expected, unreasonably low estimates of returns to scale are obtained due to a large decrease in both the capital and labor coefficient. Also the training coefficient drops substantially. However, comparing the impact of training on productivity and wages, we still find the productivity premium for trained employees to be substantially higher than the wage premium[48] and the difference is statistically significant. Estimating training impact by sector shows that again for the majority of sectors the productivity premium of trained workers is higher than the wage premium of trained workers as shown if Figure C.1. The average productivity premium across all sectors equals .10 while the average wage premium is not higher than .026. Again, we suspect these coefficients to be severely downward biased in contrast to the coefficients

received higher or university education and low-educated if he received at most primary or secundary education.

[46] These are firms that have at least 50 employees, realize a turnover of more than €7.3 million or have a total book value of their assets that exceeds €3.65 million.

[47] These figures are not reported in the table for expositional reasons.

[48] Although we suspect these estimates to be downward biased, the bias in the production function should be as large as the bias in the wage equation and thus it still makes sense to compare both estimates.

obtained by applying the Ackerberg, Caves and Frazer (2006) methodology.

Imperfect Substitution between Different Types of Workers

Up till now we have assumed that blue and white collar workers are perfectly substitutes. Here we relax this assumption. Similar to the previous subsection we divide the labor force by their training status and type of contract but now we allow the different types of workers to be imperfectly substitutable. We include two different labor aggregates in the Cobb-Douglas production function, one for blue collar workers and one for white collar workers.

$$Y_{it} = A_{it} K_{it}^{\beta_k} \widehat{L_B}_{it}^{\beta_b} \widehat{L_W}_{it}^{\beta_W} \tag{27}$$

with $\widehat{L_B}$ and $\widehat{L_W}$ the labor aggregate for blue and white collar workers respectively. Assuming the share of trained workers is constant across the different type of contact, the equation to be estimated is given by:

$$y_{it} = \beta_k k_{it} + \beta_b (l_B)_{it} + \beta_w (l_W)_{it} + (\beta_b \phi_{TB} + \beta_w \phi_{TW}) \frac{L_T}{L} + \omega_{it} + \eta_{it} \tag{28}$$

where ϕ_{TB} and ϕ_{TW} represent the productivity premium of a trained blue collar worker and the productivity premium of a trained white collar worker respectively. Now these premia are measured relative to an untrained worker with the same type of contract. The drawback of this specification is that we have to exclude all observations where there are only blue collar or white collar workers. More than 50% of all firms in the non-manufacturing sector have no blue-collar workers. Consequently, we restrict the analysis to the manufacturing sector where the vast majority of firms employ blue collar workers as well as white collar workers[49].

We estimate equation (28) applying our estimation strategy outlined in the previous section but we use two different timing assumptions. The first assumption is the same as applied before and states that both current blue collar and white collar workers are uncorrelated with contemporaneous shocks in productivity, unforeseen by the firm. However, in Belgium especially white collar

[49] Although we observe the number of managers in a firm, we opt not to include them as a seperate category because only a small percentage of firms report the number of managers. We count the number of managers as white collar workers instead. For the same reason we opt not to relax the assumption of perfect substitutability between trained and untrained employees. While it is theoretically possible to allow imperfect substitution between trained and untrained employees, we would be obliged to drop most of the observations since a large majority of the firms do not provide training to their employees.

workers are well protected against dismissal while blue collar workers face less severe employment protection legislation. Consequently there could be concerns that blue collar workers are a freely variable input that is adjusted in reaction to unforeseen productivity shocks. To control for this we also include a specification where we include blue collar workers lagged one period as instrument instead of the contemporaneous stock of blue collar workers. Results are reported in Table 13. ACF1 uses contemporaneous blue collar workers as instrument while ACF2 uses lagged blue collar workers as instrument. By comparing columns (1) and (3), one can see that the coefficient on blue collar workers goes down slightly when blue collar workers are assumed to be a freely variable input. The coefficient on the share of trained workers is somewhat lower compared to the specification where we imposed perfect substitution between the different types of workers but remains positive and highly significant. If we assume the impact of training on productivity is the same for blue and white collar workers, the estimated coefficient implies the productivity premium to be equal to 17% and 18% in the first and second specification respectively. Note that the productivity premium is larger than the wage premium, however the difference is not significant anymore. We did the same exercise for each NACE 2 digit sector separately. Results are reported in Table D.1 in the appendix. Not surprisingly, white collar workers are most important in sectors such as Chemicals, Electrical Machinery and Medical and Optical Instruments while blue collar workers receive a high weight in the production function of sectors such as Textiles, Wood Products and Motor Vehicles. The coefficient on blue collar labor goes down for the majority of sectors when assuming it is a freely variable input. However, the coefficient is mostly estimated quite imprecise.

6 Firm specific versus general training

In the previous sections, we have established a positive and both statistical and economic significant impact of training on productivity. Moreover the productivity premium was found to be larger than the wage premium. Note that this gap between the productivity and wage premium for trained employees can be explained equally well by perfect competition and firm specific training as by imperfect competition and general training. Both explanations however imply radically different policy implications. Which of the two theories is the best explanation for our results? Recall that under firm specific training the acquired skills are not applicable in other firms and the firm could pay for all training costs. The firm recoups all the benefits after training through the higher marginal product of trained workers and equal wages of trained and untrained workers. Becker (1964) noted that it could be optimal for both workers and firms to share benefits of training, namely under the form of higher wages but still lower than the marginal product. Consequently, firms are less likely to fire trained workers. Moreover, trained workers are less likely to quit the firm since skills are firm specific and they will earn lower wages at other employers. In general one would expect both dismissal and quit rates to be lower in firms that provide a substantial amount of training.

Under imperfect competition in the labor market and general training, a negative correlation between the dismissal rate and training would arise since the difference between wage and marginal product is higher for trained workers. However, when for example the presence of unions is the main source of wage compression, it is possible that training has no impact on quit rates of workers since trained workers could earn the same wage at other firms. To summarize, we would expect a negative impact of training on the dismissal rate with perfect competition and specific training as well as with imperfect competition and general training. However, with perfect competition and specific training worker quit rates should be influenced by training while this is not necessarily the case with general training and imperfect competition.

Our dataset allows us not only to compute general separation rates, but also to distinguish between whether these separations are dismissals initiated by the firm or quits initiated by the worker [50]. When we regress the quit and dismissal rates on the share of trained workers lagged one and two periods, we find that dismissal rates are negatively and significantly affected by the lagged share of trained employees[51] as can be seen from Table E.1 . Quit rates however seem to be unaffected by the number of trained workers. The coefficient on the lagged share of trained employees is not significantly different from zero[52]. The share of trained employees lagged two periods has even a positive and significant impact on the quit rates[53]. Although not a formal proof, these results suggest that the training is most likely to be general in nature instead of firm specific. Moreover,

[50] We only observe these variables for the subset of large firms.

[51] We control not only for firm fixed effects but include also inflows of employees both contemporaneous and lagged one period and year dummies to control for business cycles.

[52] The p-value is equal to .333.

[53] When aggregating training and seperation rates at the 4 digit level, there was a substantial and significant correlation between the dismissal rate and share of trained employees but not between the quit rate and share of trained employees.

recall that we observe formal training, which is more likely to be general in nature.

7 Conclusions

This paper empirically investigates the impact of firm provided training on both wages and productivity. To this end we make use of a firm level data set of more than 170,00 firms active in Belgium. We are able to measure for each firm the amount of employees that received some kind of formal training as well as the training costs and the hours spent on training for the period 1997 to 2006. The advantage of using firm level data compared to individual level data is that we obtain an objective measure for the productivity of a worker.

After controlling for the possible endogeneity of training we find that training boosts marginal productivity of an employee more than it increases its wage. More precise, our results indicate that the productivity premium for a trained employee is on average around 23% while the wage premium is only 12%. We find a slightly higher impact of training in non-manufacturing compared to manufacturing sectors. Our results are robust across different specifications and definitions of the training variable. When controlling for other sources of worker heterogeneity, our estimates for the productivity and wage premium drop to 17% and 11% respectively and the difference between the two premia remains substantial and statistically significant. Also relaxing the assumption of perfect substitutability between different types of workers leaves our main findings unaffected. There exists considerable sector heterogeneity in the impact of training on both productivity and wages. Sectors with the largest effects of training include the Chemical sector and Rubber and Plastic sector.

Our results are consistent with recent theories such as Acemoglu and Pischke (1999a) that explain firm provided general training by imperfect competition in the labor market and wage compression. This finding can have important policy implications. The standard result of Becker (1964) is that if workers are not credit constrained, training investments are efficient and as such, government intervention is unnecessary or should be directed to the credit markets. However, with imperfect labor markets and a compressed wage structure, there could be underinvestment in training from a social point of view. For example, when making their training decisions, firms do not take into account the possible externalities for future employers of trained workers (Acemoglu and Pischke

1999b). This opens possibilities for the government to implement training subsidies. However, an assessment of the optimal versus the current amount of training and the extent of government intervention to reach this optimal level lies outside the scope of this paper. We leave this for future research.

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9 Tables

Table 1: Summary Statistics

	Total	Training	No Training
Employment	16.9	84.8	6.67
Turnover (×1000€)	10,078	37,245	2,820
Labor Cost per Worker (×1000€)	35.1	44.8	33.7
Labor Productivity (×1000€)	63.9	73.0	62.5
Capital/Labor (×1000€)	75.5	69.8	76.3
Observations	919,077	54,867	864,210
Nr. Firms	171,210	15,499	155,711
Proportion of Trained Workers		0.53	
Cost of Training per Worker Trained		1,581	
Hours Training per Worker Trained		39.8	

Table 2: Summary Regressions

Dependent Var.	*(1)*	*(2)*	*(3)*	*# Obs*
Employment (ln)	2.27*		1.97*	919,077
Turnover (ln)	2.56*	0.31*	0.26*	380,091
Lab. Costs (ln)	0.36*	0.27*	0.18*	919,077
Lab. Prod. (ln)	0.24*	0.40*	0.27*	910,615
Capital/Labor (ln)	-0.27*	0.35*	0.27*	891,984

* Denotes siginificant at 1 perc. level.
(1) Regression of dependent variable on training dummy,
(2) Similar to (1) but controlling for size (employment),
(3) Similar to (2) but with NACE 4 digit dummies.

Table 3: Training by Nace 2 digit sector

NACE	Description	Nr. Firms	Employment	% Firms Providing Training	% Workers Trained	% Training Costs in Staff Costs
A	*Agriculture, Hunting and Forestry*	*2,239*	*12,078*	*1.47%*	*4.26%*	*0.06%*
1	Agriculture & hunting	2,124	11,611	1.55%	4.43%	0.06%
2	Forestry & logging	115	467	0.00%	0.00%	0.00%
B	*Fishing*	*86*	*524*	*0.00%*	*0.00%*	*0.00%*
5	Fishing & fish farming	86	524	0.00%	0.00%	0.00%
C	*Mining and quarrying*	*119*	*3,637*	*20.17%*	*32.53%*	*0.92%*
10	Mining of coal and lignite	6	53	0.00%	0.00%	0.00%
11	Extraction of petroleum and gas	1	20	0.00%	0.00%	0.00%
14	Other mining and quarrying	112	3,564	21.43%	33.19%	0.94%
D	*Manufacturing*	*14,173*	*511,012*	*12.23%*	*44.25%*	*1.20%*
15	Food products and beverages	2,539	70,322	9.77%	42.37%	0.80%
16	Tobacco products	21	1,581	33.33%	60.85%	0.92%
17	Textiles	706	28,039	17.14%	24.75%	0.59%
18	Wearing apparel	309	5,264	5.83%	18.29%	0.59%
19	Leather products	48	1,367	12.50%	28.31%	1.15%
20	Wood and wood products	600	10,482	5.67%	21.37%	0.65%
21	Pulp and paper products	228	13,625	23.68%	43.45%	0.86%
22	Publishing and Printing	1,608	25,698	8.21%	34.39%	0.70%
23	Coke and petroleum products	11	2,699	72.73%	83.07%	3.96%
24	Chemical products	496	65,767	35.08%	69.63%	1.82%
25	Rubber and plastic products	528	23,127	18.75%	40.63%	0.75%
26	Other mineral products	813	28,214	15.62%	38.20%	0.84%
27	Basic Metals	252	35,477	26.98%	56.69%	1.88%
28	Fabricated metal products	2,635	50,438	8.27%	18.65%	0.50%
29	Machinery and equipment n.e.c.	937	38,664	14.83%	48.49%	1.22%
30	Office machinery and computers	21	615	23.81%	32.52%	0.42%
31	Electrical machinery n.e.c.	287	20,630	18.47%	55.43%	1.16%
32	Radio, TV and communication	85	12,335	28.24%	66.32%	2.20%
33	Medical and optical instr.	397	6,507	8.82%	31.80%	0.86%
34	Motor vehicles	294	42,516	22.11%	61.34%	1.41%
34	Other transport equipment	136	8,436	11.03%	40.68%	1.50%
34	Furniture, manufacturing n.e.c.	1,033	16,216	6.39%	12.13%	0.36%
34	Recycling	189	2,993	9.52%	7.42%	0.20%

NACE	Description	Nr. Firms	Employment	% Firms Providing Training	% Workers Trained	% Training Costs in Staff Costs
E	*Electricity, gas and water supply*	*53*	*22,559*	*45.28%*	*78.83%*	*2.42%*
40	Electricity, gas and hot water	30	17,248	46.67%	81.55%	2.68%
41	Collection and water distribution	23	5,311	43.48%	70.01%	0.98%
F	*Construction*	*17,079*	*175,432*	*2.82%*	*9.69%*	*0.20%*
45	Construction	17,079	175,432	2.82%	9.69%	0.20%
G	*Wholesale and retail trade*	*36,150*	*374,016*	*3.93%*	*27.47%*	*0.70%*
50	Sale and repair motor vehicles	5,746	50,986	5.55%	17.03%	1.03%
51	Wholesale trade	14,166	162,870	6.01%	21.32%	0.52%
52	Retail trade	16,238	160,160	1.55%	37.04%	0.85%
H	*Hotels and restaurants*	*9,084*	*54,837*	*0.72%*	*16.69%*	*0.21%*
55	Hotels and restaurants	9,084	54,837	0.72%	16.69%	0.21%
I	*Transport, storage and communication*	*6,598*	*187,649*	*6.96%*	*37.52%*	*1.42%*
60	Land Transport; pipelines	4,205	78,416	4.19%	17.18%	0.48%
61	Water transport	96	939	7.29%	11.61%	0.23%
62	Air transport	29	4,687	20.69%	33.07%	1.87%
63	Supporting transport activities	1,839	44,674	12.72%	31.33%	1.16%
64	Post and telecommunications	429	58,933	8.39%	70.06%	2.71%
J	*Financial intermediation*	*4,240*	*24,642*	*2.88%*	*28.39%*	*1.50%*
60	Financial intermediation	1,650	12,150	2.97%	30.22%	2.18%
60	Insurance and pension funding	23	192	8.70%	5.73%	0.07%
60	Auxiliary financial activities	2,567	12,300	2.77%	26.93%	0.81%
K	*Real estate, renting, business activities*	*19,699*	*326,061*	*6.67%*	*18.84%*	*0.79%*
60	Real estate activities	2,970	13,586	3.70%	8.16%	0.15%
60	Renting activities	658	4,815	4.41%	9.49%	0.22%
60	Computer and related activities	2,431	37,417	10.51%	38.49%	1.45%
60	Research and development	82	2,993	17.07%	55.46%	1.45%
60	Other business activities	13,558	267,250	6.67%	16.39%	0.68%
	TOTAL (SERVICES AND MANUFACTURING)	109,520	1,692,447	5.19%	30.33%	0.96%

Table 4: Impact of Training on Productivity

	Total			Manufacturing			Non-Manufacturing		
	OLS1	OLS2	ACF	OLS1	OLS2	ACF	OLS1	OLS2	ACF
Labor	.785	.747	.764	.802	.767	.791	.780	.735	.751
	(.001)	(.004)	(.008)	(.003)	(.007)	(.015)	(.001)	(.005)	(.009)
Capital	.165	.123	.088	.178	.151	.129	.163	.115	.081
	(.001)	(.002)	(.004)	(.002)	(.005)	(.008)	(.001)	(.003)	(.004)
Training	.460	.315	.243	.403	.300	.215	.461	.301	.257
	(.008)	(.010)	(.010)	(.015)	(.016)	(.017)	(.008)	(.012)	(.014)
Obs	804,293	73,930	73,930	123,834	23,345	23,345	677,764	50,585	50,585
Clust	135,865	13,757	13,757	18,422	3,878	3,878	117,021	9,879	9,879

Standard errors are computed using a block bootstrap procedure with 500 replications and are robust against heteroskedasticity and intra-group correlation

Table 5: Impact of Training on Wages

	Total			Manufacturing			Non-Manufacturing		
	OLS1	OLS2	OLS3	OLS1	OLS2	OLS3	OLS1	OLS2	OLS3
Training	.438*	.200*	.167	.432*	.219*	.187*	.440*	.190*	.165*
	(.006)	(.006)	(.007)	(.009)	(.009)	(.011)	(.007)	(.009)	(.009)
ln(K/L)			-.015*			.017*			-.022*
			(.002)			(.004)			(.002)
TFP			.337*			.306*			.343*
			(.006)			(.008)			(.007)
Obs.	828,303	73,816	73,816	126581	23,318	23,318	701,722	50,498	50,498
Nr. Clusters	139,133	13,746	13,746	18759	3,878	3,878	120,374	9,868	9,868
R Squared	.134	.184	.321	.154	.221	.336	.132	.167	.309
Chi^2 $\phi_T = \lambda_T$		333.6	128.2		89.4	14.1		231.6	113.0

Standard errors are computed using a block bootstrap procedure with 500 replications and are robust against heteroskedasticity and intra-group correlation
* denotes significance at 1% level

Table 6: Results Productivity Manufacturing Sectors

	Labor		Capital		Training		Nr. Obs	
	OLS	ACF	OLS	ACF	OLS	ACF	Obs	Clust
15 Food Products	.789	.729	.175	.174	.165	.130	3,571	600
	(.018)	(.035)	(.016)	(.036)	(.031)	(.034)		
17 Textile Products	.753	.720	.154	.133	.319	.227	1,729	298
	(.027)	(.094)	(.018)	(.038)	(.042)	(.047)		
18 Wearing Apparel	.665	.675	.227	.160	.101	.049	364	66
	(.112)	(.240)	(.040)	(.094)	(.193)	(.124)		
20 Wood Products	.668	.700	.142	.102	.659	.264	588	110
	(.038)	(.266)	(.034)	(.074)	(.135)	(.106)		
21 Paper Products	.853	.658	.120	.269	.149	.036	685	98
	(.060)	(.179)	(.035)	(.099)	(.070)	(.057)		
22 Publishing	.804	.828	.103	.077	.154	.157	1,764	319
	(.027)	(.071)	(.017)	(.023)	(.064)	(.049)		
24 Chemical Products	.841	.816	.125	.116	.405	.305	2,134	331
	(.029)	(.067)	(.026)	(.047)	(.063)	(.053)		
25 Rubber and Plastic	.788	.803	.183	.172	.341	.255	1,477	227
	(.030)	(.228)	(.022)	(.064)	(.047)	(.050)		
26 Mineral Products	.798	.773	.135	.157	.219	.174	1,917	311
	(.023)	(.065)	(.020)	(.047)	(.048)	(.043)		
27 Basic Metals	.802	.772	.171	.191	.105	.084	995	146
	(.034)	(.112)	(.025)	(.049)	(.068)	(.060)		
28 Metal Products	.760	.733	.139	.129	.176	.102	2,779	478
	(.020)	(.033)	(.012)	(.016)	(.038)	(.039)		
29 Machinery	.822	.789	.114	.134	.287	.197	1,681	283
	(.034)	(.076)	(.021)	(.029)	(.051)	(.051)		
31 Electrical Machinery	.800	.745	.143	.132	.236	.219	665	104
	(.038)	(.086)	(.027)	(.059)	(.091)	(.102)		
32 Radio, TV and Telecom	.905	.894	.068	.064	.204	.151	302	54
	(.075)	(.144)	(.071)	(.102)	(.108)	(.144)		
33 Medical Eq., Optical Instr.	.813	.791	.047	.012	.256	.182	346	64
	(.074)	(.147)	(.054)	(.080)	(.101)	(.131)		
34 Motor Vehicles	.843	.776	.108	.120	.050	.087	752	121
	(.022)	(.042)	(.020)	(.027)	(.068)	(.061)		
36 Furniture, Manuf. n.e.c.	.667	.551	.184	.167	.087	.137	1,101	181
	(.039)	(.086)	(.025)	(.055)	(.057)	(.063)		

Standard errors are computed using a block bootstrap procedure with 500 replications and are robust against heteroskedasticity and intra-group correlation

Table 7: Results Productivity Non-Manufacturing Sectors

	Labor		Capital		Training		Obs.	
	OLS	ACF	OLS	ACF	OLS	ACF	Obs.	Clust.
1 Agriculture	.701	.648	.097	.132	.196	.339	459	96
	(.058)	(.077)	(.035)	(.074)	(.164)	(.134)		
14 Mining	.837	.798	.198	.267	.324	.017	345	60
	(.059)	(.250)	(.056)	(.305)	(.120)	(.143)		
37 Recycling	.737	.737	.164	.124	.239	.242	364	79
	(.071)	(.108)	(.032)	(.067)	(.135)	(.194)		
45 Construction	.774	.773	.136	.134	.184	.123	5,521	939
	(.016)	(.038)	(.010)	(.017)	(.022)	(.023)		
50 Sales Motor Vehicles	.804	.803	.091	.081	.295	.179	3,974	746
	(.019)	(.052)	(.013)	(.026)	(.042)	(.033)		
51 Wholesale Trade	.742	.758	.077	.061	.351	.317	21,380	4,017
	(.008)	(.013)	(.005)	(.006)	(.021)	(.022)		
52 Retail Trade	.779	.735	.158	.158	.125	.135	4,104	869
	(.017)	(.054)	(.012)	(.029)	(.030)	(.040)		
55 Hotels and Restaurants	.820	.798	.123	.124	.107	.084	877	164
	(.030)	(.058)	(.022)	(.047)	(.043)	(.047)		
60 Land Transport	.753	.726	.144	.147	.116	.079	2,617	455
	(.021)	(.070)	(.015)	(.043)	(.060)	(.043)		
63 Transport Activities	.633	.681	.174	.133	.305	.222	1,892	411
	(.023)	(.029)	(.015)	(.022)	(.052)	(.051)		
64 Post and Telecommunications	.753	.749	.202	.175	.283	.284	337	86
	(.049)	(.120)	(.031)	(.058)	(.175)	(.161)		
65 Financial Intermediation	.778	.766	.180	.214	.560	.453	315	79
	(.072)	(.189)	(.048)	(.123)	(.264)	(.209)		
70 Real Estate	.551	.523	.154	.090	.352	.252	1,360	275
	(.028)	(.048)	(.020)	(.040)	(.091)	(.114)		
71 Renting of Machinery	.507	.575	.367	.300	.104	.149	487	96
	(.050)	(.127)	(.051)	(.060)	(.125)	(.090)		
72 Computer and Related Activities	.855	.849	.084	.088	-.030	.002	1,587	393
	(.020)	(.026)	(.010)	(.014)	(.039)	(.046)		
74 Other Business Activities	.777	.774	.109	.093	.196	.201	4,313	975
	(.014)	(.028)	(.009)	(.015)	(.031)	(.038)		

Standard errors are computed using a block bootstrap procedure with 500 replications and are robust against heteroskedasticity and intra-group correlation

Table 8: Results Wages Manufacturing Sectors

	Training			Nr. Obs.	
	OLS1	OLS2	OLS3	Obs.	Clust
15 Food Products	.353	.155	.121	21,447	3,259
	(.021)	(.019)	(.023)		
17 Textile Products	.296	.171	.118	7,311	1,068
	(.030)	(.031)	(.040)		
18 Wearing Apparel	.702	.123	.044	3,446	535
	(.190)	(.224)	(.189)		
20 Wood Products	.290	.185	.112	5,466	787
	(.073)	(.048)	(.054)		
21 Paper Products	.372	.179	.142	2,274	300
	(.044)	(.036)	(.041)		
22 Publishing	.364	.074	.078	14,398	2,322
	(.030)	(.026)	(.029)		
24 Chemical Products	.455	.312	.242	4,774	671
	(.103)	(.032)	(.043)		
25 Rubber and Plastic	.413	.239	.212	5,027	673
	(.031)	(.025)	(.042)		
26 Mineral Products	.306	.155	.143	7,680	1,062
	(.028)	(.025)	(.028)		
27 Basic Metals	.331	.146	.112	2,627	344
	(.053)	(.048)	(.048)		
28 Metal Products	.309	.195	.157	22,864	3,340
	(.020)	(.031)	(.031)		
29 Machinery	.429	.237	.197	8,253	1,228
	(.033)	(.031)	(.038)		
31 Electrical Machinery	.342	.218	.173	2,743	408
	(.041)	(.049)	(.057)		
32 Radio, TV and Telecom	.405	.287	.248	799	128
	(.078)	(.059)	(.080)		
33 Medical Eq., Optical Instr.	.359	.104	.073	3,079	475
	(.058)	(.045)	(.054)		
34 Motor Vehicles	.264	.123	.107	2,536	367
	(.046)	(.045)	(.047)		
36 Furniture, Manuf. n.e.c.	.305	.177	.143	9,591	1,442
	(.058)	(.050)	(.056)		

Standard errors are computed using a block bootstrap procedure with 500 replications and are robust against heteroskedasticity and intra-group correlation. The number of observations refers to the first specification where all firms are included. The number of observations used in the restricted sample of Columns (2) and (3) are equal to those reported in Table 7

Table 9: Results Wages Non-Manufacturing Sectors

	Training			Nr. Obs	
	OLS1	OLS2	OLS3	Obs.	Clust
1 Agriculture	.428	.125	.145	14,077	2,424
	(.058)	(.090)	(.074)		
14 Mining	.329	.091	.050	1,126	157
	(.083)	(.069)	(.073)		
37 Recycling	.305	.267	.254	1,668	274
	(.074)	(.096)	(.095)		
45 Construction	.335	.150	.134	133,695	21,316
	(.014)	(.018)	(.019)		
50 Sales Motor Vehicles	.375	.185	.137	48,134	7,519
	(.021)	(.024)	(.027)		
51 Wholesale Trade	.468	.191	.181	120,834	19,621
	(.014)	(.013)	(.014)		
52 Retail Trade	.254	.078	.060	110,918	19,138
	(.020)	(.020)	(.025)		
55 Hotels and Restaurants	.326	.122	.104	54,774	10,545
	(.032)	(.031)	(.034)		
60 Land Transport	.195	.094	.061	35,808	5,451
	(.022)	(.029)	(.028)		
63 Transport Activities	.175	.121	.100	14,923	2,450
	(.026)	(.032)	(.034)		
64 Post and Telecommunications	.409	-.014	-.082	2,869	650
	(.067)	(.105)	(.106)		
65 Financial Intermediation	.401	.025	-.021	10,220	1,928
	(.052)	(.107)	(.115)		
70 Real Estate	.542	.303	.265	20,425	4,013
	(.042)	(.064)	(.072)		
71 Renting of Machinery	.547	.129	.084	4,971	905
	(.040)	(.059)	(.051)		
72 Computer and Related Activities	.316	-.024	-.005	15,837	3,281
	(.021)	(.031)	(.037)		
74 Other Business Activities	.409	.143	.137	90,400	17,081
	(.012)	(.021)	(.024)		

Standard errors are computed using a block bootstrap procedure with 500 replications and are robust against heteroskedasticity and intra-group correlation. The number of observations refers to the first specification where all firms are included. The number of observations used in the restricted sample of Columns (2) and (3) are equal to those reported in Table 7

Table 10: Training as Average Training Hours per Worker

	Total		Manufacturing		Non-Manufacturing		Each Sector Seperat.	
	Prod.	Wage	Prod.	Wage	Prod.	Wage.		
Capital	.090		.133		.082		β_T	
	(.004)		(.010)		(.004)		Min	-.0003
Labor	.774		.798		.759		Max	.0134
	(.007)		(.032)		(.009)		Av.	.0044
Training	.0041	.0031	.0032	.0032	.0047	.0032		
	(.0002	(.0001	(.0003)	(.0002)	(.0003)	(.0002)	α_T	
TFP		.343		.314		.349	Min	.0003
		(.005)		(.015)		(.007)	Max	.0079
Cap/Lab		-.014		.018		-.022	Av.	.0024
		(.002)		(.004)		(.002)		
Test for $\beta_T = \alpha_T$								
Chi^2	71.7		3.19		84.9			
$p-value$	.00		.07		.00			

Standard errors are computed using a block bootstrap procedure with 500 replications and are robust against heteroskedasticity and intra-group correlation

Table 11: Results Further Robustness Checks

	Total		Manufacturing		Non-Manufacturing	
	Prod.	Wage	Prod.	Wage	Prod.	Wage
Non-Linear Specification	.374	.233	.313	.259	.407	.239
SUR Model	.295	.208	.310	.225	.273	.199
	(.006)	(.005)	(.009)	(.007)	(.008)	(.006)
Wage as Control	.189	.168	.201	.178	.171	.160
	(.010)	(.006)	(.018)	(.009)	(.013)	(.008)
Lagged Training	.173	.147	.145	.168	.171	.138
	(.011)	(.007)	(.016)	(.012)	(.015)	(.010)

Standard errors are computed using a block bootstrap procedure with 500 replications and are robust against heteroskedasticity and intra-group correlation

Table 12: Worker Heterogeneity, Perfect Substitution

	Total		Manufacturing		Non-Manufacturing	
	Prod.	Wage	Prod.	Wage	Prod.	Wage.
Type of Contract ($\beta_l \phi_T$ or λ_T)	.176	.141	.173	.174	.180	.122
	(.010)	(.006)	(.015)	(.008)	(.013)	(.008)
Schooling ($\beta_l \phi_T$ or λ_T)	.152	.090	.155	.128	.149	.076
	(.010)	(.009)	(.015)	(.010)	(.013)	(.008)

Productivity estimates refer to estimation of Equations (A.5) and (A.7) and are controlled for simultaneity bias (ACF procedure).Wage results refer to estimation of Equations (A.10) and (A.11) by ordinary least squares with added control variables. Standard errors are computed using a block bootstrap procedure 500 replications and are robust against heteroskedasticity and intra-group correlation

Table 13: Blue versus White Collar Workers, Imperfect Substitution

	ACF1		ACF2	
	Prod.	Wage	Prod.	Wage
Capital	.123		.124	
	(.006)		(.006)	
Blue Collar	.360		.338	
	(.020)		(.030)	
White Collar	.439		.448	
	(.016)		(.018)	
Training	.136	.155	.138	.152
	(.015)	(.009)	(.015)	(.009)
TFP		.180		.182
		(.008)		(.008)
Cap/Lab		.029		.029
		(.003)		(.003)
Nr. Obs.	19,679		19,679	
Nr. Clust.	3,414		3,414	
Test for $\phi_T = \lambda_T$				
Chi^2	.59		1.12	
$p-value$	.44		.29	

Results ACF method with contemporaneous blue collar workers (ACF1) and blue collar workers lagged one period as instruments.
Standard errors are computed using a block bootstrap procedure with 500 replications and are robust against heteroskedasticity and intra-group correlation

Figure 1: Impact Training on Productivity and Wages

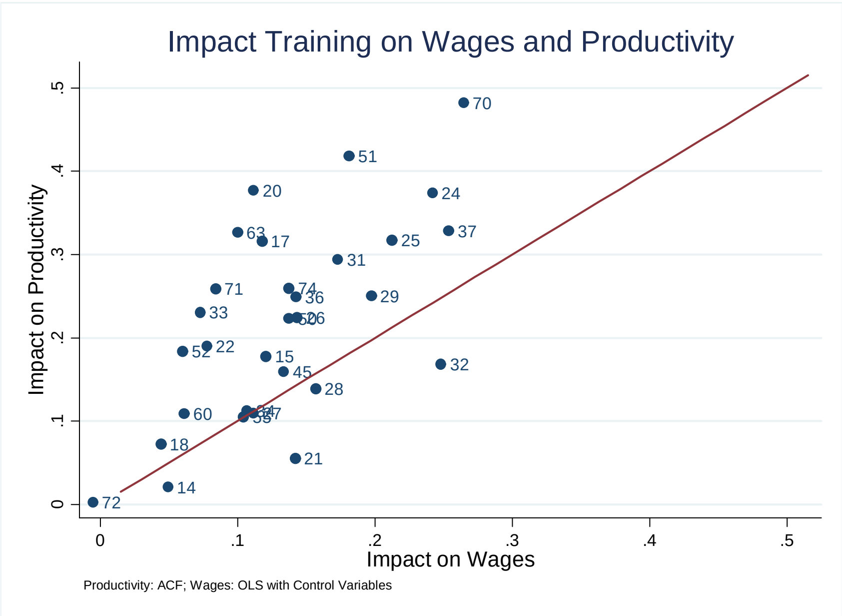
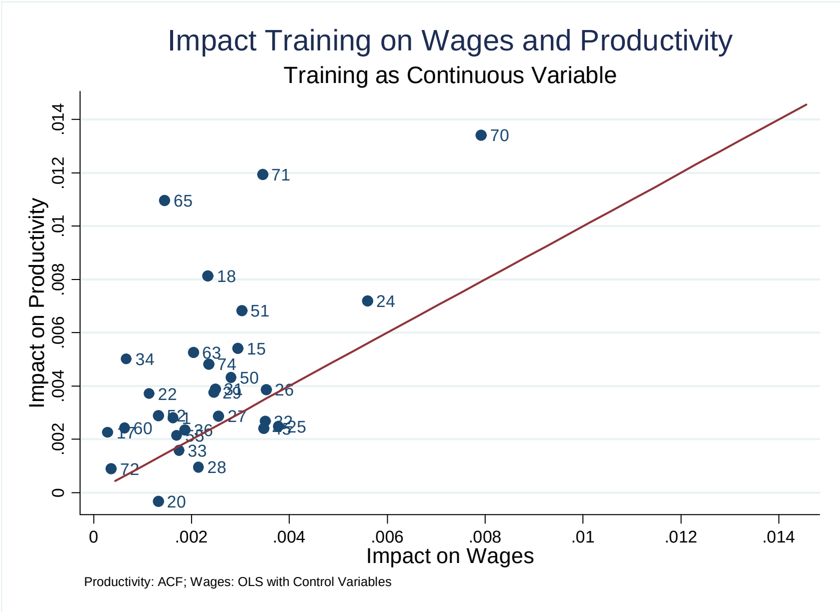


Figure 2: Impact Training on Productivity and Wages; Training as Hours Training per Worker.



Appendix

A Other sources of worker heterogeneity

A.1 Productivity

The derivations in the main text assumed that training is the only source of heterogeneity in the labor force. This appendix shows how we can generalize the expression for the labor aggregate when workers can be differentiated by multiple characteristics. Next to training we also observe whether the workers are blue collar, white collar or part of the management staff and their schooling level. When there are multiple observed characteristics, the workforce can be described by all K possible combinations of these characteristics and the labor aggregate $\widehat{L}$ can be written as:

$$\widehat{L} = L_0 + \sum_{k=1}^{K-1} (1 + \phi_k) L_k \tag{A.1}$$

where again ϕ_k is the productivity premium of a type k worker relative to a worker of the base type ($\phi_k = \frac{MP_k - MP_0}{MP_0}$). When we include for example training and the type of contract (blue collar, white collar or management) as worker characteristics, there are six different types of workers namely untrained blue collar, untrained white collar, untrained management, trained blue collar, trained white collar and trained management. If the base type is an untrained blue collar worker, then for example the relative productivity premium of a trained white collar worker, ϕ_{TW}, is defined as $\phi_{TW} = \frac{MP_{TW} - MP_{UB}}{MP_{UB}}$ with MP_{TW} the marginal product of a trained white collar worker and MP_{UB} the marginal product of an untrained blue collar worker. Again, the labor aggregate can be rewritten as:

$$\widehat{L} = L \left(1 + \sum_{k=1}^{K-1} \phi_k \frac{L_k}{L} \right) \tag{A.2}$$

or rewriting the productivity premium of a trained white collar worker, ϕ_{TW} as the product of productivity premia of white collars ϕ_W, trained workers ϕ_T and an interaction term[54] $\phi_{T \times W}$, $\phi_{TW} = \big((1 + \phi_W)(1 + \phi_T)(1 + \phi_{T \times W}) - 1\big)$ and the productivity premium of a trained manager as the product of productivity premia of managers ϕ_Z, trained workers and an interaction term $\phi_{T \times Z}$, $\phi_{TZ} = \big((1 + \phi_Z)(1 + \phi_T)(1 + \phi_{T \times Z}) - 1\big)$. When the interaction term for trained white collars is larger than zero, training of white collar workers pays off more than training of blue collar workers and the other way around when the interaction is negative. A value of zero for this parameter means that marginal productivity increases by the same amount for white collar workers as for blue collar workers in response to training. A similar reasoning applies for the interaction term of

[54] To be precise, ϕ_T represents the productivity premium of a trained blue collar worker compared to an untrained blue collar worker. Likewise, ϕ_W is the productivity premium of an untrained white collar worker compared to an untrained blue collar worker.

trained managers. The labor aggregate can be written as:

$$\begin{aligned}\widehat{L} &= L\Bigg(1+\phi_Z\frac{L_{UZ}}{L}+\phi_W\frac{L_{UW}}{L}+\phi_T\frac{L_{TB}}{L}\\ &\quad+\left[(1+\phi_Z)(1+\phi_T)(1+\phi_{Z\times T})-1\right]\frac{L_{TZ}}{L}\\ &\quad+\left[(1+\phi_W)(1+\phi_T)(1+\phi_{W\times T})-1\right]\frac{L_{TW}}{L}\Bigg)\end{aligned} \tag{A.3}$$

Note that to estimate the productivity premium of each different type of worker, we need to observe the proportion of each type in the total workforce. Unfortunately we do not observe the number of trained and untrained workers for each employee type. This forces us to make some simplifying assumptions similar to other studies that divide the labor force among several dimensions (e.g. Van Biesebroeck, 2007). First, we have to assume that he relative differences in marginal productivity between two workers that differ by one characteristic are the same irrespective of what their other characteristics are. This means that the relative marginal product of trained workers compared to untrained workers is the same for all different types of workers and consequently $\phi_{Z\times T}=\phi_{W\times T}=0$. Furthermore we restrict the proportion of one type of workers to be constant across other groups defined by the other characteristics or $\frac{L_{TZ}}{L_Z}=\frac{L_{TW}}{L_W}=\frac{L_T}{L}$. Applying these restrictions to equation A.3 gives

$$\widehat{L}=L\left((1+\phi_Z\frac{L_Z}{L}+\phi_W\frac{L_W}{L})(1+\phi_T\frac{L_T}{L})\right) \tag{A.4}$$

The expression for the production function that is taken to the data is the following:

$$y=\beta_0+\beta_k k+\beta_l l+\beta_l\phi_T\frac{L_T}{L}+\beta_l\phi_W\frac{L_W}{L}+\beta_l\phi_Z\frac{L_Z}{L}+\mu \tag{A.5}$$

Next to a specification where we make distinction between the type of contracts, we moreover divide the labor force among the schooling level and training status of the workers. Schooling is constructed such that the variable takes on two values, namely high-schooled and low-schooled. The restricted version of the labor aggregate can be written as

$$\widehat{L}=L(1+\phi_S\frac{L_S}{L})(1+\phi_T\frac{L_T}{L}) \tag{A.6}$$

where L_S is the number of high schooled workers and ϕ_S represents the productivity premium of a high-schooled worker relative to a low-schooled worker. The expression for the production function becomes:

$$y=\beta_0+\beta_k k+\beta_l l+\beta_l\phi_T\frac{L_T}{L}+\beta_l\phi_S\frac{L_S}{L}+\mu \tag{A.7}$$

A.2 Wages

In a similar way, we can extend the empirical framework for estimating wage premia by including multiple characteristics of the workforce. Imposing similar restrictions as for estimating the productivity premium, namely equal proportions and equal relative wage premia, we can write the average wage in a firm as

$$\overline{W} = W_{BU}(1 + \lambda_Z \frac{L_Z}{L} + \lambda_W \frac{L_W}{L})(1 + \lambda_T \frac{L_T}{L}) \tag{A.8}$$

where W_{BU} is the wage of an untrained blue collar worker and λ_Z and λ_W are the relative wage premia of a manager and a white collar worker. Likewise, when dividing the labor force among the schooling level and training status, the expression for the average wage becomes:

$$\overline{W} = W_{BU}(1 + \lambda_S \frac{L_S}{L})(1 + \lambda_T \frac{L_T}{L}) \tag{A.9}$$

where λ_S represents the wage premium of a schooled worker and W_{BU} is the wage of an untrained blue collar worker. Taking natural logarithms and adding control variables and an additive error term, one obtains the following equations:

$$\overline{w} = w_{BU} + \lambda_W \frac{L_W}{L} + \lambda_Z \frac{L_Z}{L} + \lambda_T \frac{L_T}{L} + X\gamma + \varepsilon \tag{A.10}$$

and

$$\overline{w} = w_{BU} + \lambda_S \frac{L_S}{L} + \lambda_T \frac{L_T}{L} + X\gamma + \varepsilon \tag{A.11}$$

These equations will be taken to the data to estimate wage premia for different types of workers.

B Monotonicity Assumption

As mentioned in Section 3 our methodology needs material demand to be monotonically increasing in productivity to invert out productivity shocks. If not, part of productivity will remain in the error term and our point estimates of the production function are likely to be biased. Moreover, our estimate for the wage premium will also likely to be biased since our measure for productivity is not picking up the whole productivity shock. In this section we will look into detail to the general conditions when the monotonicity assumption will hold.

Assume firms take both input and output prices as given and the production function is given by $Q_i = f(\widetilde{L_i}, M_i, K_i, \omega_i)$.[55] Profits of firm i are given by

$$\pi_i = pQ_i - \widetilde{w}\widetilde{L}_i - rK_i - zM \tag{B.1}$$

with r the user cost of capital and z material price. To compute the impact of a change in productivity, we assume the existence of all second order derivatives and differentiate the three first-order conditions of a profit maximizing firm with respect to productivity. We obtain the following system of equations[56]:

$$\begin{pmatrix} f_{LL} & f_{LM} & f_{LK} \\ f_{ML} & f_{MM} & f_{MK} \\ f_{KL} & f_{KM} & f_{KK} \end{pmatrix} \begin{pmatrix} \partial L/\partial\omega \\ \partial M/\partial\omega \\ \partial K/\partial\omega \end{pmatrix} = \begin{pmatrix} -f_{L\omega} \\ -f_{M\omega} \\ -f_{K\omega} \end{pmatrix} \tag{B.2}$$

and one can use Cramer's rule to obtain a solution for $\partial M/\partial\omega$. By the second-order condition for maximization the matrix in the denominator must be negative semidefinite and consequently its determinant is negative. Hence the sign of $\partial M/\partial\omega$ is equal to minus the sign of the determinant in the numerator:

$$\begin{aligned} sign(\frac{\partial M}{\partial\omega}) &= -sign(-f_{LL}f_{M\omega}f_{KK} - f_{L\omega}f_{MK}f_{KL} - f_{K\omega}f_{ML}f_{LK} \\ &\quad +f_{KL}f_{M\omega}f_{LK} + f_{LL}f_{K\omega}f_{MK} + f_{ML}f_{L\omega}f_{KK}) \end{aligned} \tag{B.3}$$

and consequently $\partial M/\partial\omega$ is positive if

$$\begin{aligned} &f_{LL}f_{M\omega}f_{KK} + f_{L\omega}f_{MK}f_{KL} + f_{K\omega}f_{ML}f_{LK} \\ &-f_{KL}f_{M\omega}f_{LK} - f_{LL}f_{K\omega}f_{MK} - f_{ML}f_{L\omega}f_{KK} > 0 \end{aligned} \tag{B.4}$$

Note that optimizing behavior implies that the marginal product of an input decreases in that particular input, i.e. $f_{LL} < 0$ and $f_{KK} < 0$. Moreover if we assume the marginal product of one input to be increasing in usage of an other input and the marginal product of each input to be increasing in productivity ω, $\partial M/\partial\omega$ will be positive if $|f_{LL}f_{M\omega}f_{KK}| + |f_{L\omega}f_{MK}f_{KL}| + |f_{K\omega}f_{ML}f_{LK}| + |f_{LL}f_{K\omega}f_{MK}| + |f_{ML}f_{L\omega}f_{KK}| > |f_{KL}f_{M\omega}f_{LK}|$, which is likely to be satisfied for most production technologies.

Intuition becomes more straightforward if capital is assumed to be a fixed input that does not respond to productivity. It can be shown in a similar way

[55] Instead of writing production as a function of untrained and trained workers, we write it as a function of the labor aggregate. Under the assumption of perfect competition in the labor market and perfect substitution between trained and untrained workers, the firm will only use trained employees if the wage premium is lower than the productivity premium and the other way around if the wage premium is larger than the productivity premium.

[56] We drop the subscript i and the tilde on the labor aggregate for the ease of notation.

(cf. Levinsohn and Petrin, 2003) that the following condition must be satisfied for $\partial M/\partial\omega$ to be positive

$$f_{L\omega}f_{ML} - f_{LL}f_{M\omega} > 0 \tag{B.5}$$

Again, f_{LL} must be negative and assume the marginal products if labor and materials are increasing in ω. Consequently, the condition will always be satisfied if $f_{ML} \geq 0$, namely if the marginal product of materials weakly increases in labor. Note that the condition will still hold if $f_{ML} < 0$, but depends on the relative magnitudes in the right-hand side of Equation B.5. When also labor is fixed and does not respond to productivity shocks, the only requirement for material demand to be increasing in productivity is that the marginal product of materials increases with productivity.

Now if condition (B.4) holds everywhere, it holds that:

$$M(\omega_1;.) > M(\omega_2;.) \quad \text{if } \omega_1 > \omega_2 \tag{B.6}$$

and material demand will be monotonically increasing in productivity.

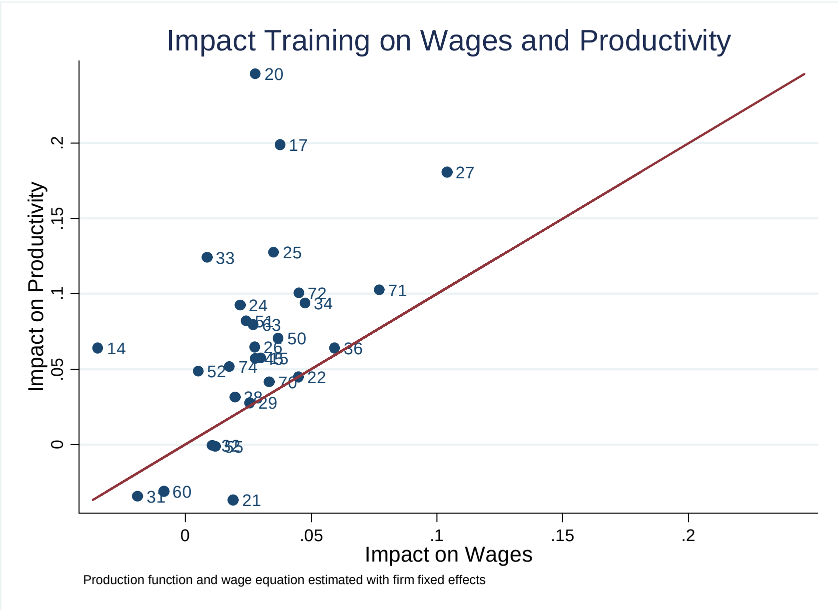
Note that we have assumed firms to be price takers in input and output markets. When for example firms set markups over marginal costs in the output market, the conditions for the material demand function to be monotonically increasing in productivity, change. Intuitively, with imperfect competition in the output market, it is possible that firms do not increase output in response to a positive productivity shock. This because increasing output puts downward pressure on the output price. For more on this we refer to De Loecker (2007).

C Fixed Effects

Table C.1: Fixed Effects Regression

	Total		Manufacturing		Services		Each Sector Separately	
	Prod.	Wage	Prod.	Wage	Prod.	Wage.		
Capital	.064		.067		.063		ϕ_T	
	(.002)		(.003)		(.002)		Min	-.037
Labor	.668		.688		.661		Max	.36
	(.003)		(.006)		(.004)		Avg.	.096
Training	.044	.025	.048	.031	.042	.023	λ_T	
	(.005)	(.003)	(.008)	(.004)	(.006)	(.004)	Min.	
Cap/Lab		.027		.028		.026	Max.	-.044
		(.001)		(.002)		(.001)	Max.	.104
							Avg.	.026
Nr. Obs.	88,357	89,991	27,271	27,519	61,086	62,472		
Test for $\phi_T = \lambda_T$								
Chi^2	24.3		7.5		15.1			
$p - value$	.000		.006		.000			

Figure C.1: Impact Training on Productivity and Wages: Fixed Effects.



D Imperfect Substitution between Blue and White Collar Workers; Sector Heterogeneity

Table D.1: Blue collar and white collar workers; per NACE 2 digit sector

	Blue Collar		White Collar		Capital		Training		Nr. Obs	
	ACF1	ACF2	ACF1	ACF2	ACF1	ACF2	ACF1	ACF2	Obs	Clust
15 Food Products	.411	.421	.381	.377	.155	.155	.090	.088	3,191	557
	(.034)	(.108)	(.035)	(.044)	(.021)	(.021)	(.028)	(.030)		
17 Textile Products	.485	.457	.293	.305	.126	.126	.153	.154	1,509	273
	(.145)	(.252)	(.045)	(.105)	(.021)	(.020)	(.042)	(.046)		
18 Wearing Apparel	.218	.218	.495	.495	.065	.064	.008	.008	295	58
	(.610)	(.808)	(.221)	(.273)	(.078)	(.087)	(.156)	(.173)		
20 Wood Products	.261	.232	.404	.414	.068	.069	.340	.345	483	102
	(.341)	(.528)	(.109)	(.197)	(.028)	(.030)		(.187)		
21 Paper Products	.540	.512	.357	.371	.088	.091	.090	.093	630	95
	(.272)	(.330)	(.105)	(.117)	(.031)	(.036)	(.061)	(.060)		
22 Publishing	.233	.417	.064	.145	.116	.103	.081	.096	1,042	194
	(.335)	(.544)	(.133)	(.171)	(.025)	(.034)	(.078)	(.094)		
24 Chemical Products	.234	.230	.577	.579	.145	.145	.131	.131	1,714	275
	(.056)	(.325)	(.053)	(.111)	(.031)	(.035)	(.051)	(.048)		
25 Rubber and Plastic	.440	.465	.395	.381	.157	.156	.175	.176	1,331	211
	(.068)	(.225)	(.049)	(.079)	(.019)	(.023)	(.042)	(.049)		
26 Mineral Products	.464	.462	.349	.350	.082	.082	.138	.138	1,676	284
	(.064)	(.155)	(.049)	(.051)	(.031)	(.033)	(.041)	(.043)		
27 Basic Metals	.288	.172	.439	.497	.074	.077	.112	.114	893	135
	(.202)	(.399)	(.098)	(.122)	(.041)	(.039)	(.073)	(.068)		
28 Metal Products	.414	.256	.290	.324	.098	.102	.100	.104	2,426	436
	(.209)	(.303)	(.035)	(.062)	(.018)	(.018)	(.038)	(.038)		
29 Machinery	.347	.350	.495	.494	.103	.103	.154	.154	1,481	257
	(.100)	(.375)	(.081)	(.104)	(.022)	(.027)	(.051)	(.058)		
31 Electrical Machinery	.213	.167	.552	.586	.038	.037	.196	.207	587	97
	(.104)	(.315)	(.068)	(.087)	(.026)	(.028)	(.064)	(.068)		
33 Medical Eq., Optical Instr.	.316	.357	.590	.562	.049	.047	.268	.266	255	49
	(.166)	(.282)	(.255)	(.259)	(.056)	(.060)	(.133)	(.134)		
34 Motor Vehicles	.619	.630	.272	.264	.068	.067	.137	.140	640	112
	(.135)	(.248)	(.115)	(.120)	(.033)	(.033)	(.072)	(.081)		
36 Furniture, Manuf. n.e.c.	.449	.406	.344	.364	.073	.072	.079	.081	898	157
	(.239)	(.651)	(.096)	(.135)	(.034)	(.036)	(.055)	(.090)		

Results ACF method with contemporaneous blue collar workers (ACF1) and blue collar workers lagged one period as instruments. Standard errors are computed using a block bootstrap procedure with 500 replications and are robust against heteroskedasticity and intra-group correlation

E Training and Separation Rates

Table E.1: Seperation rates and training

	FE one lag		FE 2 lags	
	Dismissals	Quits	Dismissals	Quits
Train. $\text{Share}_{t\text{-}1}$	-.00254*	-.00132	-.0028*	-.0023
	(.0015)	(.0024)	(.0015)	(.00241)
Train. $\text{Share}_{t\text{-}2}$			.00174	.00627**
			(.00149)	(.00237)
Nr. Obs	76,359	76,359	76340	76340

Firm and year fixed effects included
* $p < 0.10$, ** $p < 0.05$