Do Foreign Experts Increase the Productivity of Domestic Firms?

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Abstract: Sometimes only the best is good enough. This is the point of departure of the O-ring theory by Kremer (1993). In this paper we extend the theory to show that domestic firms may want to hire foreign experts as they offer highly specialised skills. In the empirical section we apply data for employees in Danish companies who are taxed according to a special tax beak offered to foreign experts. We find that it is the most productive firms that hire foreign experts. In the year before a firm hires foreign experts, TFP is around 40% higher than in other firms. In the manufacturing sector there is also a 15% increase in TFP after the firm hires foreign experts. In contrast, within the service sector, there is no significant increase in TFP after a firm hires foreign experts. However, as a robustness check we also use firm specific wages as a measure of productivity. Applying this measure, we find that productivity increases in both sectors when firms hire foreign experts.

1. Introduction

Despite widespread restrictions on international migration of labour, most countries welcome highly qualified immigrants. Some countries even subsidise immigrants if their qualifications are sufficiently high. In, *e.g.*, Denmark, Sweden and The Netherlands, foreign labour with sufficiently high qualifications (called "foreign experts" in what follows) are offered special tax breaks. An important question is therefore whether these experts are in fact particularly valuable for the host countries?

The employment of foreign experts may lead to different types of gains for the host country, including higher tax revenue. In this paper, however, we restrict attention to potential productivity effects. In other words, do foreign experts play an important role in raising the productivity in the host country firms in which they are hired? We address this question by considering the development in productivity in the Danish companies employing tax-subsidised foreign experts.

One reason why foreign experts may be important for firms' productivity is that sometimes a high quality of a produced good requires the input of highly specialised skills in certain tasks of the production process, and it may be easier to find foreign labour with these particular skills – in particular in a small country like Denmark, Sweden or the Netherlands. That sometimes "only the best is good enough" is actually the point of departure of the so called O-Ring-theory by Kremer (1993). The theory got its name from some components – the O-rings – used in the space shuttle Challenger. Although this space shuttle had thousands of high-quality components, the fact that the O-rings did not function properly caused the shuttle to explode. This example is, of course, rather extreme, but it illustrates that very strong complementarities between different tasks in the production process may exist; and only one badly performed task may ruin the value of all the other tasks.

Below we extend the O-ring-theory to the case of human experts to illustrate how a few foreign experts in a company may be important for the realised productivity. The idea is that a firm that uses high-quality inputs in a number of tasks sometimes stands to gain a lot from being able to attract an expert with very specific qualifications. Hence, to achieve a high productivity in a firm, it may be necessary to employ foreign experts.

In the empirical section of the paper, we consider whether the use of foreign experts do in fact increase total factor productivity (TFP). A foreign expert is defined as an employee in a Danish company who are taxed according to a special tax break offered to foreign experts. First, it turns out that TFP is much higher in firms which use foreign experts than in other firms – actually around 40% higher. Second, we consider whether the increase in productivity is higher in firms which hire foreign experts than in other firms. To do this analysis we apply a diff-in-diff matching approach (see e.g. Heckman, Ichimura and Todd, 1997 or Blundell and Costa-Dias, 2009). It turns out that within the manufacturing sector, there is a large and significant increase (15%) in TFP in firms which hire foreign experts.

Since there are well known methodological problems in estimating TFP, we also apply wages as an alternative measure of firms' productivity. The hypothesis is that firms with higher productivity also pay higher wages. However, when using wages, we still find that, within manufacturing TFP is higher in firms which hire foreign experts than in other firms, but the increase is now more modest (between 1% and 4%).

Within service industries the picture is more blurred. The increase in TFP is not significantly higher in firms which hire foreign experts than in other firms. However, when using wages as a measure of productivity, hiring foreign experts has an effect on productivity which is similar to what is the case within manufacturing.

There is a substantial literature on how immigrant workers affect wages and employment of native workers; see, *e.g.*, Card (1990, 2001) and Borjas (2003). However, in most of these studies, immigrants "simply" increase the labour supply. The studies do not consider the possibility that foreign experts may play a special role with respect to affecting the productivity of firms. One exception is Markusen and Trofimenko (2009) who set up a theoretical model where foreign experts may teach local employees new "tricks" and in this way increase their productivity. Using data on Columbian firms, they find that the use of foreign experts increases firm productivity and the wages of the local employees.

The idea that foreign experts raise the productivity of local workers by teaching them new "tricks" seems most relevant when considering foreign experts in developing countries. Our model, on the other hand, suggests that firms achieve a better match between the optimal skills and the actual skills when they are able to employ foreign experts. This possibility seems relevant for firms in developed countries as well as in developing countries.

The rest of the paper is structured as follows. In Section 2, we present the theoretical model. Section 3 outlines the empirical framework, and section 4 presents the data used. Section 5 contains the empirical analysis, and Section 6 concludes.

2. Theory

Our point of departure is the O-Ring Theory by Kremer (1993). We follow Kremer by assuming that the production process in a firm consists of *n* different tasks performed by skilled labour. The firm may affect the input in a specific task by the choice of the skill level – or the quality level – of the workers employed to perform that task. The cost for the firm of a higher skill level is a higher wage.

We extend the model by Kremer (1993) by introducing another dimension in the quality of a worker employed to perform a specific task. Specifically, we assume that among workers with a certain *level* of skills as evaluated by the market (the vertical dimension), workers differ with respect to how well their specific *types* of skills fit the needs of a given firm (the horizontal dimension).[1] An example could be two persons who both hold an MBA from a prestigious business school, and both have 10 years of management experience from a company. However, one of the two has experience from managing a private hospital, while the other has experience from managing a construction company. Despite the fact that both persons are highly qualified managers, their specific types of skills do not fit equally well into all firms.

Different job experiences in the past is only one reason for differences in skill types between individuals with the same skill level, other reasons for such horizontal variation may be specialization across schools or different personal characteristics. Hence, if the firm wants a worker with a higher skill level (as in the model by Kremer), the firm has to pay a higher wage. However, among workers at a certain skill level, and therefore at a certain

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[1] It could be argued that this dimension is implicitly a part of the quality level in Kremer (1993), but we want to distinguish between the quality level as evaluated by the market (vertical differentiation), and the need for specific skills which varies between firms (horizontal differentiation).

wage level, workers differ with respect to how well their skill types fit the needs of a specific firm.

To formalise these ideas, the production in firm j is assumed to be given as the outcome of the following production function:

$$y_j = A_j k_j^{\alpha} h_j^{\beta} l_j^{\gamma} \tag{1}$$

where A_j is an exogenous productivity parameter, k_j is capital, h_j is the input of skilled labour, and l_j is the input of unskilled labour.[2]

Building on Kremer (1993), we assume that the use of skilled labour is organised around a number of tasks in the firm, with the total input of skilled labour given by:

$$h_j = \left(\Pi_{i=1}^{n_j}\left(q_{ij} \cdot (1 - d_{ij}\right)\right) \cdot s_j \tag{2}$$

where s_j is the number of skilled workers, n_j is the number of tasks in firm j, q_{ij} is the (average) skill level of the workers in task i ($0 \leq q_{ij} \leq 1$), and d_{ij} is the (average) distance between the optimal skill type and the actual skill type in task i ($0 \leq d_{ij} \leq 1$). In Kremer (1993), d_{ij} is implicitly equal to zero. Since s_j is the number of employed skilled workers, s_j/n_j is the number of replications of the required tasks in the firm. To simplify the exposition, we assume that n_j is exogenous and does not vary across firms, $n_j = n$.

Note that, if for all i, $q_{ij} = 1$ and $d_{ij} = 0$, then $h_j = s_j$ which is the highest possible input of skilled labour if the firm hires s_j skilled workers. In this case, the workers have the highest

[2] In the empirical specification, we actually distinguish between three skill levels of labour.

possible skill levels as measured by q_{ij} (the vertical dimension), and their skill types perfectly match the needs of the firm as measured by d_{ij} (the horizontal dimension).

In the following, total factor productivity (TFP) is defined as the part of the productivity of the firm which is not explained by the quality of the inputs of the firm, *i.e.*, TFP is a measure of our *ignorance*.[3] Ideally, the only part of the production function to be included in TFP is the Hicksian shift parameter, A_j. However, in practice, it will typically not be possible to measure the extent to which the firm has success in hiring candidates with the optimal skill types, *i.e.*, there will not be information on the d_{ij}'s. If this information is not available, the impact of the skill types will instead show up in the observed TFP of the firm. Furthermore, although it is often possible to obtain information about the skill level of the workers, we often do not have the required information about the number of tasks to correct for this in the measurement of TFP. Hence, the impact of the q_{ij}'s will also show up in the observed TFP.

With this in mind, and by inserting (2) into (1), we can express the production function as:

$$y_j = TFP_j \cdot k_j^{\alpha} \cdot {s_j}^{\beta} \cdot l_j^{\gamma} \tag{3}$$

where TFP_j is "observed" TFP given by:

$$TFP_j = A_j \cdot \left(\Pi_{i=1}^{n} q_{ij} \cdot \left(1 - d_{ij}\right)\right)^{\beta} \tag{4}$$

[3] Total factor productivity measures “unexplained” shifts in the production function arising from, *e.g.*, technical innovations, and organisational and institutional change. Hulten (2000) discusses different concepts and problems related to defining and measuring TFP.

Even though we are not able to observe the extent to which the firm has success in attracting skilled workers with the optimal types of skills, the firm can still spend resources on diminishing the d_{ij}'s. One thing the firm can do is to extend its search for suitable experts to the international market. We will assume that such searching involves a firm-specific fixed cost, c_j^f.

If the price of the good produced by the firm is normalized to one, the variable profit of the firm (excluding any fixed costs of searching for foreign experts) is given by:

$$\pi_j = y_j - \left(\sum_{i=1}^{n} w_i(q_{ij}) + \sum_{i=1}^{n} c_i(E_j, d_{ij})\right) \cdot {}^{S_j}/_{n} - w^u \cdot l_j - r \cdot k_j \qquad (5)$$

where $w_i(q_{ij})$ is the wage cost of getting a worker for task i of quality q_{ij}, w^u is the unskilled wage, and r is the cost of capital. Wages and capital costs are assumed exogenous. $c_i(E_j, d_{ij})$ is the cost of getting a skilled worker for task i where the distance between the optimal type and the actual type hired is d_{ij}, and E_j is a measure of the extent of the market in which firm j searches for skilled workers.[4] Specifically, we shall assume that:

$$c_i(E_j, d_{ij}) = E_j \cdot (1 - d_{ij})^{n+1} \qquad (6)$$

Hence, if the firm wants a better match, there is a higher cost, *i.e.*, $\frac{\partial c_i}{\partial d_{ij}} < 0$. Furthermore, the marginal cost of improving the match increases as the match gets closer to the optimal

[4] To be precise, q_{ij} is the *average* quality of workers in task i, and d_{ij} is the *average* distance between the optimal skill type and the actual skill type in task i. Hence, strictly speaking, $w_i(q_{ij})$ is the wage cost per worker of getting workers with an *average* quality of q_{ij} for task i, and $c_i(E, d_{ij})$ is the cost per worker of getting skilled workers for task i with an *average* distance of d_{ij} between the optimal and the actual types of skills in task i.

match, $\frac{\partial^2 c_i}{\partial d_{ij}^2} > 0$.[5] However, if the firm gets access to a larger market for skilled labour (represented by a smaller value of E_j), it is able to get the same match at a lower cost, *i.e.*, $\frac{\partial c_i}{\partial E_j} > 0$. Furthermore, access to a larger market decreases the cost of improving the match, $\frac{\partial^2 c_i}{\partial E_j \partial d_{ij}} < 0$.[6]

In the following, we assume that there are only two possible levels of the extent of the market for skilled labour:

$$E = \begin{cases} D & \text{if the firm can use only native skilled workers} \\ I & \text{if the firm can use foreign and native skilled workers} \end{cases}$$

where $D > I$. Hence, if the firm has paid the fixed cost of searching for experts internationally, it faces lower variable costs of obtaining workers with skills of a given distance from the optimal type of skills, $c_i(I, d_{ij}) < c_i(D, d_{ij})$. Furthermore, it is less costly to improve the match quality when firms can search internationally, $\frac{\partial c_i(D, d_{ij})}{\partial d_{ij}} < \frac{\partial c_i(I, d_{ij})}{\partial d_{ij}} < 0$.

In the following, we shall focus on the horizontal dimension in the task quality. Hence, we assume that $q_{ij} = 1$ for all i and j, and that $w_i(1) = w^s$ for all i. Under the assumption of decreasing returns to scale in all production factors, $n\beta + \beta + \alpha + \gamma < 1$, the following proposition characterises the resulting equilibrium of the model.

[5] The marginal cost also increases with n reflecting that a larger number of different tasks makes it harder to obtain a better match within a given task.

[6] More realistically, the *probability* of getting a better match should increase with the extent of the market. However, to keep the analytics tractable, we assume that the match improves with certainty. This assumption does not affect the results qualitatively.

Proposition 1

1. *There exist a critical value of the fixed cost as a function of A_j: $\bar{c}(A_j)$ where $\bar{c}'(A_j) > 0$, and such that firm j will employ foreign experts if and only if $c_j^f < \bar{c}(A_j)$.*
2. *A firm j with $c_j^f < \bar{c}(A_j)$ will have a higher observed TFP than another firm k with $A_k = A_j$ and $c_k^f > \bar{c}(A_k)$.*
3. *A firm j will have a higher observed TFP than another firm k with $c_k^f = c_j^f$ and $A_k < A_j$.*

Proof: See Appendix.

The Proposition is proved formally in the Appendix, but the implications are the following: If firms are distributed across $(A_j - c_j^f)$-space according to some distribution, then in equilibrium, firms in the south-east corner will choose to search for and hire foreign experts. These are firms which have a low fixed cost, c_j^f, of hiring foreign experts and/or a high exogenous TFP level, A_j. The importance of the latter follows from the complementarity between exogenous TFP and the quality of the match, and the fact that a better match can be obtained more easily (cheaper) at the international market. This is the first part of the Proposition 1.

As a consequence, if two firms have similar levels of exogenous TFP, but only one of them has a fixed cost below the critical value, then only this firm will hire foreign experts. It will also have a higher observed TFP, as the use of foreign experts results in an improved match (lower d_{ij}'s) between the optimal types of skills and the actual types of skills employed in the firm, *cf.* Equation (4). This is the second part of Proposition 1.

However, differences in exogenous TFP can also lead to differences in the use of foreign experts and observed TFP. First, a higher A_j will impact directly on observed TFP. Second, the higher A_j will increase the likelihood of employing foreign experts, which will result in a better match. The better match will in turn also contribute to a higher observed TFP. This is the last part of Proposition 1.

Note also that a higher observed TFP (whether due to A_j or c_j^f) raises the marginal product of the other production factors. Hence firms with higher observed TFP will be bigger in terms of employment and capital. Therefore, it is more likely that foreign experts are employed in large firms.

The next proposition contains some comparative statics results which follow in a straightforward manner from the equilibrium conditions above.

Proposition 2

1. *A decrease in c_j^f (or an exogenous increase in A_j) increases the likelihood that firm j hires foreign experts and increases its observed TFP.*
2. *A decrease in the cost of capital and/or the wage rates may cause additional firms to hire foreign experts and increase their observed TFP.*

Proof: See Appendix.

A drop in the firm-specific cost of searching for foreign experts or an exogenous increase in TFP may both cause a firm to start hiring foreign experts. In both cases, the firm will also realise a higher observed TFP. But only in the former case can the increase be attributed entirely to the foreign experts (or the cost of these, to be precise). In the latter case, the higher observed TFP is only caused by the foreign experts, but there is a strong complementarity between the use of foreign experts (the endogenous part of TFP) and the exogenous part of TFP, as explained in connection with Proposition 1, part 2.

Finally, a change in one of the other parameters (the cost of capital or one of the wage rates), may also cause some firms to start using foreign experts and increase their observed TFP. The reason is that, *e.g.*, a lower cost of capital increases the use of capital which improves the value of a better match and hence the incentives for searching internationally. This is due to the complementarity between foreign experts and the other production factors.

3. Empirical framework

The two propositions from the previous section lead directly to two empirical predictions that we test on Danish data:

I. Under most distributions of c_j^f and A_j (*i.e.*, except when they are strongly positively correlated), firms that use foreign experts have on average higher observed TFP and are larger.

II. If a firm starts to use foreign experts, then this should be associated with an increase in observed TFP compared to another firm with same initial level of observed TFP

The first prediction follows from Proposition 1 under the assumption that firms with high exogenous TFP do not in general have higher costs of searching the international job market than other firms. The prediction concerns the (static) cross-sectional distribution of firms and is investigated in Section 4 by considering how the use of foreign experts is related to different firm characteristics using simple descriptive statistics.

The second prediction follows directly from Proposition 2, and concerns the dynamic changes in observed firm productivity associated with the hiring of foreign experts. Note that the reason to start using foreign experts can be either an idiosyncratic change in c_j^f (or a discovery of the value of c_j^f by the firm) or A_j or a general change in the wages or the cost of capital, cf. Proposition 2.

To test this prediction, we should compare changes in observed TFP between firms that hire foreign experts and firms that do not, i.e. a diff-in-dif approach. A simple diff-in-diff estimation will give a first indication of the validity of this prediction. However, as the prediction concerns initially identical firms, a more appropriate test of this prediction is to use a diff-in-diff matching estimator, where we match on initial observed TFP, see Heckman, Ichimura and Todd (1997) and Blundell and Costa-Dias (2009) for a recent exposition of the diff-in-diff matching estimator.

In this case, let $D_{jt} \in \{0,1\}$ be an indicator of whether firm *j* hires foreign experts at time *t*, and let TFP_{jt}^1 denote total factor productivity at time t if the firm hired foreign experts at time t, whereas TFP_{jt}^0 is TFP if it did not hire foreign experts. The impact of hiring foreign experts on firm j is then defined as $\Delta_{jt} = TFP_{jt}^1 - TFP_{jt}^0$. The fundamental evaluation problem is that we do not observe the same firm with both outcomes at the same point in time. Instead we may switch attention to constructing means and define the change in TFP in firms using foreign experts (which in the literature is called "the average effect of treatment on the treated" (ATET)) as

$$\delta = E[TFP^1 - TFP^0 \big| D=1] = E[TFP^1 \big| D=1] - E[TFP^0 \big| D=1] \tag{7}$$

That is, the problem is to find the counterfactual $E[TFP^0 \big| D=1]$ which is unobserved. We solve this problem by using matching techniques.

According to the theoretical model, it would be sufficient to match on initial TFP, because it determines the values of all the other variables. However, in reality where we do not have a perfect measure of TFP, we get a better match by also matching on other variables. Matching with many covariates leads to a dimensionality problem, so we use the propensity score method (Rosenbaum and Rubin, 1983) to summarise the vector of characteristics, X, into a single-index variable, the propensity score $P(X)$. We estimate the propensity score using a probit model. We discuss in detail later the choice of variables included in the probit model.

So in the following we focus on the difference in outcomes before and after hiring foreign experts. In this case the matching difference-in-differences estimator (MDID) takes the following form

$$\delta_{MDID} = \frac{1}{N_1} \sum_{j \in I_1 \cap S_P} \left(\Delta TFP_j - \sum_{i \in I_0} W(i,j) \Delta TFP_i \right), \tag{8}$$

where ΔTFP_j denotes the difference between TFP before and after hiring foreign experts, and I_1 and I_0 are the sets of treatment and comparison firms respectively. N_1 is the number of firms in the set $I_1 \cap S_P$, where S_P denotes the common support region of the propensity score. The weights, $W(i, j)$ are constructed such that they depend on the distance in propensity scores between firm *j* and firm *i*. We implement two different matching estimators to construct the weights; the standard nearest neighbor matching estimator, where only one comparison firm is used (the one with the propensity score closest to the treatment firm), and local linear regression matching where multiple comparison units are used (where the weights are inversely proportional to the distance).

4. Data and foreign experts in Denmark

We have access to a very rich matched worker-firm longitudinal data set – the socalled FIDA dataset – covering the total Danish population of workers and firms for the years 1999-2006. Each individual and each firm is associated with a unique identifier, and, crucially, all employed individuals are linked with a firm identifier at the end of each year.

Detailed information on individual socio economic characteristics is available on an annual basis. There is information about e.g. age, sex, citizenship, labor market experience, tenure, education and a wage rate calculated as annual labor income divided by annual hours. These individual level variables are extracted from the integrated database for labour market research (IDA) and the income registers in Statistics Denmark.

To this matched worker-firm dataset we add information from the Account Statistics Register about firm size defined as the number of full-time employees, capital stock defined as the value of land, buildings, machines, equipment and inventory, value added defined as revenues net of input costs and, finally, energy consumption. From the matched workers we can distinguish between different skill levels of the workers, which allows us to calculate the total factor productivity (TFP) of firms. The productivity variable is estimated following the Levinsohn and Petrin (2003) procedure – see the appendix for more details.

4.1 Foreign experts in Denmark

Finally, we merge information from the Danish tax authorities about firms hiring foreign experts that are eligible for reduced taxation under the "Tax scheme for foreign researchers and key employees". This scheme was introduced in 1992 and applies a flat-rate tax of 25 %, which is much lower than the normal tax rates in the Danish tax system (the highest marginal tax rate was around 60% in the period under consideration). The scheme was changed in 2002. Before 2002, foreign experts were eligible for the reduced tax rate for the first three years, but if they stayed in Denmark more than seven years, they were liable to pay a reimbursement tax equivalent to the subsidy obtained in the first three years. In 2002 this reimbursement tax was abolished such that the foreign experts can now stay in Denmark as long as they wish without paying any additional taxes to compensate for the subsidy in the first three years.

To be eligible for the reduced tax rate some requirements must be met. The most important ones are the following. First, the employee should not have been liable to pay taxes in Denmark for the previous three years. This implies that not only foreigners but also Danes who have stayed abroad for more than three years may be eligible for the reduced tax rate. However, the second requirement is that it does not count as years abroad if a person was expatriated by the current employing company. Third, the monthly salary of the person should be above a threshold level which in 2006 was 63696 Danish kroner (corresponding to around 8500 Euro). Hence, this threshold level of income is effectively what defines an expert – i.e. a person who has a sufficiently high productivity to command this salary.

It should be mentioned that foreign experts may be eligible for the low tax rate, even if they are not paid a wage above the threshold level. There is no requirement to the level of income if the foreign expert is employed by a university or a research institution. However, in the following we restrict attention to the foreign experts employed in private companies, where they are all required to have a wage higher than the threshold level.

In Figure 1, we illustrate the development in the number of foreign experts in private firms. It is a relatively low number of employees who by our definition are foreign experts. In 1999 there were around 1200, and this number has increased to around 1600 in 2006. There seems to be an upward shift in 2004, and one possible explanation of this may be the change in the tax scheme in 2002.

INSERT FIGURE 1 HERE

Table 1 illustrates the distribution of the foreign experts over origin countries in 1999 and 2006. The countries are ranked according to the share of foreign experts originating from the countries in 2006. The rank in 1999 is given in the second column. First, we note that in 2006, 26% of the foreign experts originated from Denmark. Hence, these are Danish employees who have been working abroad for at least 3 years prior to the current employment. In 1999 only 6% of the foreign experts originated from Denmark. A likely explanation behind this increase in the share of “foreign experts” originating from

Denmark is the change in the program in 2002. It may be more valuable for Danes than for other foreign experts that they can stay in Denmark for more than seven years without paying back the subsidy obtained in the first 3 years.

The other main suppliers of foreign experts to Danish firms are the neighbouring countries Germany and Sweden – followed by UK and USA. In 2006 all other countries each contributed with less than 5% of the foreign experts.

INSERT TABLE 1 HERE

Table 2 illustrates the distribution of foreign experts over industries. The industries are ranked according to their share of the foreign experts in 2006. It is somewhat surprising that in 1999, 25% of the foreign experts were employed within whole sale – in 2006 the share was 18%. The other industries employing many foreign experts are R&D intensive industries, and industries where the quality of the good may depend on the input of very specialized skills. This is definitely the case within chemicals and medical products, data processing and research, but also in the other industries employing foreign experts.

INSERT TABLE 2 HERE

4.2 Firms with foreign experts

Table 3 displays the number of private sector firms with and without foreign experts. It is clear that only a minority of the firms have foreign experts in their workforce. Less than 400 firms have foreign experts out of around 18000 private sector firms.

INSERT TABLE 3 HERE

The last column of Table 3 shows the number of firms that start using foreign experts. These firms will constitute the observations in the treatment group in the matching analysis, and they are defined in the following way. A firm is classified as hiring foreign experts for the first time, if, first, it is observed in at least five consecutive years: year -1, 0, 1, 2 and 3. Second, the firm did not employ foreign experts in the base year (year 0) or the previous year (year -1)or earlier sample years but were observed with at least one foreign expert among its employees in the following year (year 1).

A firm enters the comparison group if it is observed in at least five consecutive years as above and did not employ any foreign experts in these years or earlier sample years. Notice, this means that a firm can enter the comparison group with multiple observations with different base years.

Firms that start hiring foreign experts are different from firms without foreign experts. Table 4 reports the results of simple regressions where the dependent variable is a firm characteristic measured in the base year and the explanatory variable is the treatment indicator. It is seen that firms with foreign experts are bigger, have higher sales, export more, use more high skilled labor and capital, are more productive and pay higher wages. For example, TFP is 41% higher in the base year for firms that start hiring foreign experts the following year. These differences persist when including industry fixed effects and firm size as additional controls.

INSERT TABLE 4 HERE

The differences suggest that selection effects play an important role. Firms that hire foreign experts were already more productive on average to begin with than firms that do not hire foreign experts. Table 4 indicates the need to appropriately control for these selection effects.

5. Results

The theoretical model in section 2 gave the clear prediction that TFP should be higher in firms using foreign experts than in other similar firms. In this section, we consider whether there is empirical evidence in support of this prediction.

5.1 Descriptive evidence

Before we turn to the matching analysis, it is instructive to consider some simple cross-industry comparisons between firms using foreign experts and firms that do not use foreign experts. Table 4 showed that firms that hire foreign experts are initially more productive and this is true for all one-digit industries, see Table 5. However, the productivity differences exhibit substantial variation across industries with manufacturing of food, textiles and leather showing the largest differential of 73%.

INSERT TABLE 5 HERE

There may be historical unobserved reasons why TFP is higher in some firms than in others. To control for that, we compare the change in TFP between the year before the firms hire foreign experts and the year after to the similar change for firms that do not hire foreign experts, see Table 5. This exercise corresponds to a simple difference-in-differences regression without controlling for other time varying firm characteristics. What we see is that firms in some industries – notably manufacturing industries – appear to become more productive from hiring foreign experts while firms in other industries do not. It is however interesting to note that for those industries where the two years change in TFP is negative, are industries where there is a high initial level of TFP in firms employing foreign experts. Hence, the negative effect may arise because TFP is not measured very precisely. Because we only have a limited number of firms in the treatment group we will only distinguish between two broad sectors in what follows: manufacturing (the three first industries in Table 5) and service.

5.2 A matching analysis

The simple analysis above suggests that there may be complementarities between productivity and foreign experts as predicted by the theory. However, there may be other explanations behind this correlation. In particular there may be other characteristics of a firm that both explain the productivity and the use of foreign experts. It is for example well known that large firms are more productive and pay higher wages than small firms (see e.g. Oi and Idson, 1999). Productivity is found to be higher in firms using more educated labor through spillover effects. For example, Mas and Moretti (2009) find positive productivity spillovers from the introduction of highly productive personnel into a shift, and Battu et al. (2003) find a positive effect on own earnings of co-worker education. It is also a stylized fact that exporting firms are more productive than other firms (see e.g. Bernard and Jensen (1995) and Bernard et al. (2007)). It seems likely that at least some of these other explanations behind a high TFP may be correlated with the incentive to employ foreign experts, and if these other characteristics vary over time the simple DID estimator above will likely be biased.

In addition, if the effect of hiring foreign experts is heterogeneous across firms, which is suggested by Table 5, then it becomes important to carefully select an appropriate comparison group of firms that do not hire foreign experts. For example, a simple linear DID would also produce biased estimates even if firm characteristics such as size, education level and export sales were controlled for. Therefore, in this section we use the MDID estimator as described in section 3.

The first step in applying the MDID estimator is to predict the propensity scores for all firms in the sample. In estimating the probit model we include a number of firm characteristics measured in the base year (i.e. the year before hiring foreign experts). As argued above we control for firm size (measured both in terms of the number of full time employees and firm sales), the quality and composition of factor inputs (shares of high and medium skilled workers in the workforce, average wages and capital) and exports divided by sales. In essence, by matching on these variables we indirectly also match on base year TFP. In so doing firms in principle only differ initially with respect to their firm specific fixed search costs for foreign experts, c_j^f.

Table 6 shows the results of estimating the probit model for manufacturing and service firms respectively. Different characteristics appear to matter for the selection into hiring foreign experts in the two sectors, but firm sales has a highly significant positive impact on the hiring probability. If the sales variable is omitted from the model firm size instead picks up the positive size effect.

INSERT TABLE 6 HERE

Having predicted the propensity scores from the probit models above, the next step is to evaluate the quality of the match obtained by implementing the two matching estimators as described in section 3. Our identifying assumption is that, conditional on the propensity scores, the outcomes of interest, TFP^1 and TFP^0, are independent of selection into treatment. This implies that the base year firm characteristics should be balanced between the treatment and control groups. Table 7 displays the standardized bias for the variables in the probit models, which is one way to evaluate the quality of the match. It is seen that local linear regression matching seems to do the best job in the manufacturing sector, while nearest neighbor matching works best in the service sector. It is also clear that matching generally reduces the bias substantially for all variables, and that the treatment and comparison groups are comparable after matching.

INSERT TABLE 7 HERE

It should be noted that the common support restriction implies that we lose two firms in the manufacturing treatment group and three firms in the service treatment group. This is a limited loss of observations, but these firms are characterized by being relatively large.

Next, we estimate the effect of hiring foreign experts using the MDID estimator. We first consider the impact on the change in firm level TFP. For example, the results for t=1 in Table 8 indicates the effect of hiring foreign experts on the change in TFP between time period 1 (the year where foreign experts are hired) and 0 (the year just before). We find no significant effect on this outcome for any of the sectors. However, if we consider the change in TFP between period 2 and 0 or 3 and 0 there are significantly positive effects in the manufacturing sector. The local linear regression matching estimator performed best in terms of balancing the treatment and control groups in the manufacturing sector, and here TFP is around 15% higher after two or three years. This is a quite sizeable effect and suggests that the hiring of foreign experts indeed help improve the productivity of manufacturing firms. In contrast, we find no significant impacts on TFP in the service sector in any of the periods.

INSERT TABLE 8 HERE

5.3 Firm and worker level wages

We only had a limited number of observations in the two treatment groups, and there are well known methodological problems in estimating the TFP outcome variable, so it would be reassuring with some additional evidence in support of the performance improving effects associated with hiring foreign experts. As a robustness check we therefore turn our attention to wages as an outcome variable. Higher productivity in a firm should manifest itself in higher wages for the employees for example as a result of rent sharing. There is ample evidence for this relationship, see e.g. Blanchflower et al. (1996), Hildreth and Oswald (1997) and Arai (2003). Table 8 also reports the effects of hiring foreign experts on firm level average wages in the three periods considered before. Considering the results for local linear regression matching for the manufacturing sector, we find that wages increase by around 2 % in period 3. Using the nearest neighbour matching estimator we find almost 4 % higher wages in the service sector in period 3. These results are borderline significant.

We can exploit the wealth of information in our matched worker-firm data even further. Even if we condition on the composition of workers in terms of educational attainment, there may still be selection of different worker types into the treatment and control firms along other dimensions. To circumvent this we go to the worker level in the following, where we can control for many individual level variables such as labor market experience, tenure in the firm, age, marriage and immigrant status

Table 9 shows the treatment effects on the full sample of workers remaining in their firms in the two sectors. In manufacturing we find a modest but significantly positive effect of 0.7% of hiring foreign experts in period 3. There are significantly positive effects in the service sector in all three periods increasing to 1.2% in period 3.

INSERT TABLE 9 HERE

6. Conclusion

Sometimes only the best is good enough. This is the point of departure of the O-ring theory by Kremer (1993). This theory suggests that it may be important for a firm to have access to highly specialized inputs in order to get a sufficiently high quality of the final output. In this paper we have extended this theory to include foreign experts defined as employees in Danish companies taxed according to a special tax break offered to foreign experts. Our theory suggests that firms which extend their searching for experts to foreign markets increase the probability of getting a good match between their specific needs of expertise and the qualifications of the employed experts in the firm. This implies that there is a strong complementarity between the employment of foreign experts and the productivity of the firm, and the hiring of foreign experts is at least partly responsible for a high productivity.

In the empirical section of the paper, it is tested whether the productivity, measured as TFP, is indeed higher in firms hiring foreign experts. We find that it is the most productive firms which hire foreign experts. In the year before a firm hire foreign experts, TFP is around 40% higher than in other firms. However, within manufacturing there is also a 15% increase in TFP after the firm hire foreign experts. Since there are methodological problems in estimating TFP, we apply wages as an alternative measure of productivity. Again, it turns out that within manufacturing there is a significant increase in wages after the firm employs foreign experts, but the increase is now only between 1% and 4%.

Within the service sector we do not find a significant effect on TFP of hiring foreign experts. This may be due to the problems in estimating TFP which may be particularly severe within the service sector. Moreover, when using wages as our measure of productivity, there is a significant increase in productivity in firms within the service sector of a similar size as within manufacturing.

Appendix A: Proof of Propositions

To be added

Appendix B: Estimation of TFP

Estimation of TFP at the firm level requires information about firm level inputs and outputs which are retrieved from the Danish Account Statistics register. From this register we get information about firm size defined as the number of full-time employees, capital stock defined as the value of land, buildings, machines, equipment and inventory, value added defined as revenues net of input costs and energy consumption. From the matched workers we will distinguish between two types: low and high-skilled labor, where low-skilled is defined as workers with just primary education, while high-skilled workers have a secondary or tertiary education. We could use a finer skill group definition, but that would mean more firms with zero employees in at least one skill group, and such observations would then have to be dropped from the TFP calculations. For that reason we settle for a distinction between high and low-skilled labor.

To calculate TFP one typically assumes a Cobb-Douglas production function, and given that we observe firm level value added, V, capital, K, high skilled labor input, H, and low skilled labor input, L, this amounts to the following log form regression:

$$\log V_{it} = \gamma_0 + \gamma_K logK_{it} + \gamma_H logH_{it} + \gamma_L logL_{it} + \varepsilon_{it},$$

where the measure for TFP for firm i at time t may be retrieved as the estimated residuals ε_{it} plus the estimate of the constant, γ_0. We deflate value added by an industry level price index for ten different manufacturing industries and four different service industries.

A well-known challenge in TFP calculations is to account for unobserved productivity shocks that are correlated with factor usage by the firm, see e.g. Olley and Pakes (1996). Failure to do so will lead to biased production function coefficients and bias in the TFP measure as a result. To correct for endogeneity bias we apply the Levinsohn and Petrin (2003) methodology and use energy consumption as a proxy for productivity shocks. Different technologies across industries are allowed for by estimation of the production function for fourteen different industries. This yields coefficients on the capital input variable, γ_K , in the range between 0.036 and 0.114, the high-skilled labor input variable, γ_H , in the interval 0.268 to 0.742, and the low-skilled labor input variable, γ_L , in the interval 0.059 to 0.452.

The estimated TFPs (i.e. γ_0 plus ε_{it}) is merged to our dataset described in section 4 as our firm measures of productivity.

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Table 1. Origin country shares of foreign experts, 1999 and 2006

Country	1999	1999 rank	2006
Denmark	0,063	7	0,264
Germany	0,075	6	0,138
Sweden	0,156	2	0,129
UK	0,175	1	0,090
USA	0,098	3	0,074
Norway	0,079	5	0,044
France	0,086	4	0,041
Netherlands	0,051	8	0,038
Finland	0,041	9	0,021
Japan	0,013	13	0,017

Note: Information about citizenship was only available for 73 and 81 percent of the foreign experts in 1999 and 2006, respectively

Table 2. Industry shares of foreign experts, 1999 and 2006.

Industry	1999	1999rank	2006
Wholesale trade	0,245	1	0,185
Consultancy	0,113	3	0,178
Chemicals and medical products	0,070	4	0,116
Financial products	0,044	6	0,099
Data processing	0,055	5	0,077
Research	0,036	8	0,045
Apparatus for e.g. measurement	0,017	13	0,038
Windmills and electronics	0,003	26	0,033
Machines	0,034	9	0,025
Prosessed food products	0,023	12	0,021

Note: The industries are based on the two digit NACE classification.

Table 3. Number of Danish private sector firms with and without foreign experts.

Year	All firms	With experts	Newly hired
1999	17509	279	
2000	18274	260	62
2001	18019	333	35
2002	17673	298	38
2003	17245	289	68
2004	17456	378	
2005	17842	392	
2006	18428	381	

Note: The sample includes manufacturing and service firms with at least 10 employees, positive factor inputs and value added. A firm is classified as hiring foreign experts for the first time, if it is observed in at least two consecutive years, the base year and the previous year, and did not employ foreign experts in any of these years or earlier sample years but were observed with at least one foreign expert among its employees in the following year. Furthermore we also condition on the firm being observed the three years following the base year.

Table 4. Characteristics of firms hiring foreign experts

Firm size (number of employees)	449,81	
Share high skilled	0,16	0,10
Share medium skilled	-0,10	-0,05
Share low skilled	-0,06	-0,05
Log capital	1,62	0,67
Log sales	1,92	0,81
Export/sales	0,21	0,13
Log average wage	0,23	0,15
Log TFP	0,41	0,21
Controls	None	Size and industry fixed effects

Note: The coefficients are from regressions of the firm characteristic in the first column on the treatment indicator for hiring foreign experts the following year.

Table 5. TFP and change in TFP for firms hiring foreign experts by industry

One digit NACE industry	Log TFP	Two year change	Number of treated
Manufact. of food, textiles and leather	0,7263	-0,0111	10
Manufact. of wood, chemicals and metal	0,0556	0,0836	36
Electricity, gas and water supply	0,1046	0,4861	12
Wholesale and retail trade	0,4143	0,0142	87
Transport, storage and communication	0,4289	-0,0433	15
Financial intermediation, business activities	0,4059	0,0638	41

Note: The coefficients are from regressions of log TFP in the base year before hiring foreign experts or the change in log TFP between the post and pre hiring year on the treatment indicator. Construction has been left because we are not allowed to publish cells wit less than five firms

Table 6. Probit models to estimate the propensity score, firm sample.

	Manufacturing			**Service**		
	Coeff.	Std. Err.	P > z	Coeff.	Std. Err.	P > z
Firm size	0,0002	0,0004	0,658	0,0001	0,0001	0,621
Firm size squared	0,0000	0,0000	0,817	0,0000	0,0000	0,749
Share high skilled	0,3426	0,5589	0,540	0,6549	0,2604	0,012
Share medium skilled	-0,6677	0,4912	0,174	-0,2925	0,2899	0,313
Log capital	-0,0076	0,0537	0,887	0,0575	0,0251	0,022
Log sales	0,4077	0,0875	0,000	0,2841	0,0359	0,000
Export/sales	0,2718	0,1626	0,095	0,5196	0,1143	0,000
Log average wage	0,5645	0,4587	0,219	1,0470	0,1704	0,000
Industry dummies	Yes			Yes		
Year dummies	Yes			Yes		
Pseudo R squared	0,29			0,24		
Observations	19936			22297		
Treatment obs.	60			143		
Control obs.	19876			22154		

Notes: A firm belongs to the treatment group if it is observed in at least two consecutive years, the base year and the previous year, and did not employ foreign experts in any of these years or earlier sample years but were observed with at least one foreign expert among its employees in the following year. Furthermore we also condition on the firm being observed the three years following the base year. The explanatory variables are from the base year.

Table 7. Quality of the match, firm sample.

Manufacturing sector

Variable	Nearest neighbor				Local linear			
	Mean		%		Mean		%	
	Treated	Control	Bias	Reduction	Treated	Control	Bias	Reduction
Firm size	348,79	317,41	3,0	94,2	348,79	336,44	1,2	97,7
Firm size squared	330000,00	310000,00	0,2	99,0	330000,00	360000,00	-0,3	98,7
Share high skilled	0,20	0,20	1,5	98,2	0,20	0,20	4,8	94,3
Share medium skilled	0,41	0,42	-5,9	92,1	0,41	0,41	-1,8	97,6
Log capital	10,73	10,56	11,1	93,1	10,73	10,66	4,3	97,3
Log sales	12,42	12,33	7,3	96,2	12,42	12,36	5,1	97,4
Export/sales	0,50	0,52	-7,8	93,0	0,50	0,50	-1,7	98,5
Log average wage	5,26	5,27	-2,1	97,4	5,26	5,26	1,3	98,4

Service sector

Variable	Nearest neighbor				Local linear			
	Mean		%		Mean		%	
	Treated	Control	Bias	Reduction	Treated	Control	Bias	Reduction
Firm size	153,53	152,33	0,1	99,7	153,53	169,17	-1,0	96,2
Firm size squared	84836,00	240000,00	-0,5	96,9	84836,00	350000,00	-0,9	94,8
Share high skilled	0,33	0,32	2,8	96,6	0,33	0,31	8,7	89,2
Share medium skilled	0,37	0,37	1,2	96,9	0,37	0,38	-4,2	89,3
Log capital	9,31	9,33	-0,6	99,1	9,31	9,19	6,7	90,2
Log sales	11,99	2,02	-2,0	98,5	11,99	11,89	8,2	93,8
Export/sales	0,27	0,28	-2,2	96,7	0,27	0,26	5,7	91,5
Log average wage	5,44	5,44	0,8	99,2	5,44	5,42	9,3	91,4

Notes: The standardized bias for a given variable is defined as the difference in means between the treated firms and the matched comparison group scaled by the average variances, see Smith and Todd (2005).

Table 8. Treatment effects, firm samples.

	Nearest neighbor		Local linear	
	ATET	T-stat.	ATET	T-stat.
Manufacturing sector				
Log TFP at t=1	0,0253	0,45	0,0323	0,71
Log TFP at t=2	0,1915	1,98	0,1575	1,91
Log TFP at t=3	0,2045	2,25	0,1528	2,00
Log avg. wage at t=1	0,0129	1,09	0,0095	1,06
Log avg. wage at t=2	0,0303	2,37	0,0161	1,54
Log avg. wage at t=3	0,0366	2,59	0,0207	1,93
Service sector				
Log TFP at t=1	0,0299	0,52	-0,0452	-1,03
Log TFP at t=2	0,0874	1,61	0,0478	1,15
Log TFP at t=3	0,0994	1,57	0,0296	0,61
Log avg. wage at t=1	0,0078	0,69	0,0127	1,51
Log avg. wage at t=2	0,0141	0,93	0,0264	2,23
Log avg. wage at t=3	0,0374	1,78	0,0385	2,40

Table 9. Treatment effects, worker samples.

	ATET	T-stat.
Manufacturing sector		
Log wage at t=1	-0,0076	-0,78
Log wage at t=2	-0,0005	-0,20
Log wage at t=3	0,0072	2,63
Service sector		
Log wage at t=1	0,0075	3,34
Log wage at t=2	0,0076	2,82
Log wage at t=3	0,0120	3,76

Note: All treatment effects are calculated using nearest neighbor matching

Figure 1. Number of foreign experts in manufacturing and service industries