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Impact of R&D Activities of Firms on Productivity: Findings from an Econometric Study of the Turkish Manufacturing Sector

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Impact of R&D activities of firms on productivity. Findings from an econometric study of the Turkish manufacturing sector

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Abstract

In this paper we are investigating the following question for Turkey: "How does the increase in R&D capital stock and how do foreign knowledge spillovers affect labor productivity?" Our sample is composed of R&D performers only, hence the Heckman two stage procedure with the instrumental variables technique for panel data is implemented (Semykina and Wooldridge, 2010). Appropriate instruments are used in regressions for the endogenous variables. Our findings signal that the indigenous efforts of R&D performers and their physical capital stock intensity exert a positive effect on firm-level labor productivity. However, neither foreign ownership nor foreign knowledge spillovers are found to affect R&D performers' labor productivity positively. On the other hand, skill exerts a strong positive impact on productivity, pointing to the significant role of educated staff in R&D performing firms. We can conclude that Turkish R&D performers are dependent on their accumulated physical capital stock intensity and their own R&D efforts when it comes to increasing labor productivity.

1. Introduction

Today the significant role of R&D activities in the development of economies is accepted by many countries. In order to survive in the tough competition, many firms engage in R&D. They expect a positive impact on their own performance from this rather uncertain and very expensive investment. However due to the non-rival nature of R&D, others who do not conduct R&D also benefit from the knowledge spilling to the environment. Thus many papers on the effect of R&D and productivity take into account both the direct effect and the spillover effects. (Mairesse and Sassenou, 1991, Wieser 2005) It is the goal of this paper to study the effect of R&D on the Turkish manufacturing firms, considering both the direct and indirect effects of R&D activities.

After a brief description of the R&D expenditures in Turkey, a literature review will be presented in section 1. The contribution and the hypothesis will be presented in sections two and three respectively. Empirical model will be presented next. Data cleaning and variables' description will be provided in section five, which will be followed by methodology and the estimation results in sections seven and eight. Finally conclusion will be presented in section 8.

The R&D activities in Turkey have been rising. Depicting the R&D performance of Turkey Figure 1 reveals that while gross domestic expenditure on R&D as a percentage of GDP was as low as 0.37 in 1998, after 2003 it has been increasing and reached 0.73 in 2008.

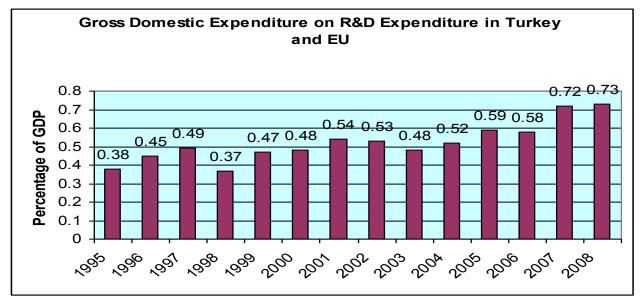


Figure 1. Gross Domestic Expenditure on R&D in Turkey

Source: Eurostat.

During the same timeframe another interesting development has occured with respect to the R&D expenditures of the business enterprise sector. As presented in Figure 2, since 2004 the R&D expenditures of the business enterprise sector has been rising at the expense of the R&D expenditures of the higher education sector.

Research and Development Expenditures in Turkey by Sectors of Performance 0.80 Percentage of GDP 0.60 0.40 0.20 0.00 2000 2001 2002 2003 2004 2005 2006 2007 2008 Years ■ Business Enterprise ■ Higher Education □ Government

Figure 2 Research and Development Expenditures in Turkey by Sectors of Performance

Source: Turkish Institute of Statistics.

The rising role of the business enterprise sector is also visible from Figure 3 where the financing of R&D expenditures by the business sector is exhibited. Turkey still lags behind the EU27 with 0.35% of GDP defining the magnitude of R&D financed by business enterprises. On the other hand there is a significant gap in favor of Turkey in terms of growth rates of R&D. Between 2003 and 2007, Turkish business enterprises' financing of R&D expenditures grew by more than 100% while that of the EU27 grew by only 2.9 %. This significant gap in growth rates also underlines the growing role of the business enterprise sector in R&D activities in Turkey.

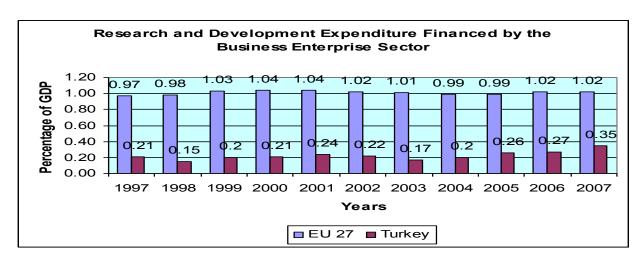


Figure 3 Research and Development Expenditure Financed by the Business Sector

A look at the labor productivity of R&D performers and non performers in Figure 4 indicates that the R&D performers are by far better off than the non performers. The increase in the labor productivity of R&D performers is much higher than that of the nonperformers. At this point a natural question to ask is the following? "Could higher R&D spending be a factor in explaining this improved productivity?" which is the question this paper tries to answer. Taking into account other control factors such as increased

foreign ownership and knowledge spillovers, this paper examines the impact of R&D capital stock on labor productivity for Turkish manufacturing firms from 2003 to 2007.

AverageLabor Productivity of R&D performers versus others 10.8 Natural logarithm of Labor 10.6 10.4 productivity 10.2 R&D performers 10 Non-performers 9.8 9.6 9.4 9.2 2003 2004 2005 2006 2007

Figure 4 Average Labor Productivity of R&D Performers and others

Source: Turkstat

2. Literature Review

Ever since the seminal paper of Griliches in 1979, the effect of R&D on productivity has been researched by quite a number of people. Most of the time, a production function of Cobb Douglas form has been used to study the effect of R&D on productivity (Mairesse and Sassenou 1991, Wieser 2005, Hall et. al. 2010):

$$Q_{it} = AK_{it}^{\alpha}L_{it}^{\beta}R_{it}^{\gamma}S_{it}^{\mu}e^{\varepsilon_{it}}$$

where Q represents the output, A the technical progress, K physical capital stock, L labor, R R&D capital stock of the firm and S stands for the knowledge stock of the environment surrounding the firm. α , β are elasticities with respect to physical capital and labor. γ and μ are elasticities with respect to firm's own knowledge capital and the knowledge pool in the environment. t is the time index. ε_{it} stands for any errors in the specification.

When logs of this production function is taken, it turns into a linear form which yields

$$\ln Q_{it} = \eta_i + \lambda_t + \alpha \ln K_{it} + \beta \ln L_{it} + \gamma \ln R_{it} + \mu \ln S_{it} + \varepsilon_{it}$$

Here we assume that the log of technical progress can be written as the sum of firm specific effect η_i and time effect λ_i . Although in economic growth theory `A' stands for the level of knowledge or technology representing the contribution of R&D to the level of knowledge of the firm, some researchers do not use it at all, while others use it without defining it. When A is used in the equation it

represents the effect of external factors to the firm. (Hall and Mairesse 1995). Reviewing the literature one finds that many issues have been raised measuring returns to R&D investment. In the following these will be presented as found in the literature.

1.1 Measurement of output

Griliches (1979) claims that much of R&D is performed in industries where the product is poorly measured and quality improvement can not be properly observed in the product. In defense, health and space industries output measures are generated from input measures. For instance in space industry, R&D output is measured as man hours and the output's quality does not depend on the success of a mission where the new spaceship is used. In defense, products are sold to the government and there are no price indices that take into account the improved performance of the chips or the new warfare.

In consumer product producers, there is the additional problem of considering the competition in pricing their products. As most consumer firms are not pure monopolists, they can not reflect the social returns to their products. Most of the time, these innovative products are introduced at slightly higher prices. Therefore, the innovating firm can only partially appropriate the return to its R&D investment. The price indices are not adjusted for the quality improvement. Thus, what is reflected in the price indices is only the private return reflected in the price. As social returns are not captured in prices, the output of R&D falls short of reflecting the full returns to R&D. Consequently, the R&D output's value is underestimated. Griliches (1979) calls this the measurement of output problem and points out that there is not much to do about it. However, Mairesse and Mohnen (1985), and Hall et.al. (2010) claim that if panel data is used with industry and time dummies, the quality problem in the measurement of output is mitigated to a certain extent.

Regarding output measurement, another issue is the price deflators. Most of the time aggregate price indexes at the two digit level are used by researchers rather than firm level deflators. While some researchers (Wieser 2005) find this not appropriate, others report very small differences between results when using sector specific versus a single deflator for the whole economy.(Harhoff, 1998) In a recent literature review article Hall et.al (2010) indicate which deflator one uses does not make much of a difference.

1.2 Measurement of inputs

As R&D expenditures also have capital, labor and material costs components, when one uses R&D expenditures as another factor of production in the production function one runs into the risk of counting them twice. As a result of this double counting problem, wrong input measures emerge. (Wakelin, 2001) The bias can be either positive or negative as reported by a number of researchers. (Hall and Mairesse (1995), Harhoff (1994)) The sign of the bias depends on the increase or decrease in R&D intensity.(Hall et. al.2010).

Another point that needs to be considered with inputs regards the different kinds of labor, with different skills and educational levels. Hall, et.al. (2010) cite three studies in French Mairesse and Cunéo (1985), Mairesse and Sassenou (1989), and Crépon and Mairesse (1993) that obtain lower R&D coefficients when they introduce different skilled labor variables to their production functions. This is

attributable to the high correlation between highly educated labor and R&D. However, this is a problem that one runs into in the cross sectional dimension rather than the within dimension because quality of labor does not change much over time. As far as capital another significant input is concerned one factor that can be considered to reduce the quality problem could be age. Yet again when age is introduced to as a measure of capital quality Hall et.al. (2010) indicate that there is not much improvement in the R&D coefficients.

1.3 Capital stock

Knowledge is a difficult concept to measure. Particularly the contribution of science to knowledge is almost impossible to measure. However, what has been done so far in the literature is the measurement of the contribution of industrial investment in R&D. To that end, the most frequently preferred method of making use of the available R&D flow information at the firm level is the perpetual inventory method as proposed by Griliches (1979). This method assumes R&D capital stock is composed of previous R&D flows in time as in the following:

$$K_t = RD_t + (1-d)RD_{t-1} + (1-d)^2 RD_{t-2} + \dots = RD_t + (1-d)K_{t-1}$$

where K_{t-1} is the knowledge capital at the end of year t and RD_t are the real R&D expenditures during year t and d is the depreciation rate which is assumed to be constant. In other words, according to this method current stock of knowledge is the result of present and past R&D expenditures discounted by a rate of depreciation. This approach also has problems of its own.

1.4 Depreciation

The depreciation rate in the above presented perpetual inventory method is assumed to be known, yet in reality it is unknown. However the literature suggests that one can assume that the private depreciation rate is higher than the social depreciation rate. (Griliches, 1979) The private depreciation rate is that applied to a single firm's knowledge capital and the social depreciation rate is the one applied to a whole sector of firms' knowledge capital. Secondly, depreciation is assumed to be constant in the perpetual inventory method. This means a portion of the R&D stock becomes obsolete every single year whether R&D is performed or not. However this is a debatable issue according to Wieser (2005) who claims that "most economists would agree that knowledge does not depreciate in such a mechanical way" (p.592). Furthermore in the above formulation depreciation is taken as exogenous. Yet Griliches (1979), Capron and Cincera (1998), Hall et. al. (2010) indicate depreciation is not exogenous. It depends on firstly firm's own behavior, secondly on its competitors' behaviors and thirdly on the general progress of science and technology. This fact also adds another reason not to accept the depreciation rate as constant.

When one uses a depreciation rate to construct the R&D capital stock, one also assumes a lag structure which reflects the distribution of R&D effects in time. Since it is not realistic to assume that the current R&D stock affects productivity right away, it makes sense to introduce some lags. While Ravenscraft and Scherer (1982) claim a lag structure between 4 to 6 years is appropriate Griliches and Mairesse (1984) point out that after two years, the lag effect loses its impact and lag structure does not matter much in

cross sectional regressions. These findings render lag structure and depreciation problematic issues to deal with. Notwithstanding these difficulties, a number of researchers have tried to find the appropriate depreciation rate by trying different rates in the construction of knowledge stock. Griliches and Mairesse (1984), Hall and Mairesse (1995), Harhoff (1994) and Bernstein and Mamuneas (2006), find a range of values from about 8% to 29%.

Given the difficulties in computing the R&D capital stock, another approach has been devised to use R&D intensity rather than R&D capital stock. This approach makes sense for instance with cases where a country is at the beginning of RD process, and it does not posses much of an R&D stock. Therefore the R&D expenditures are more important in the generation of the R&D stock per se. (Griliches and Mairesse 1985) This approach makes use of the relationship between the elasticity of R&D investment and rate of return on R&D investment. Initially the productivity equation is restated in growth form as in the following:

$$\Delta q_{it} = \Delta a_{it} + \lambda + \alpha \Delta k_{it} + \beta \Delta l_{it} + \gamma \Delta r_{it} + v_{it}$$

Next making use of the definition of the elasticity of R&D investment which is

$$\gamma = \frac{\partial Q}{\partial R} \frac{R_{it}}{Q}$$

A transformation is performed from the elasticity to rate of return on R&D investment by multiplying elasticity with the growth of RD capital investment.

$$\gamma \Delta r_{it} = \frac{\partial Q}{\partial R} \frac{R_{it}}{Q_{it}} \frac{\Delta R_{it}}{R_{it}}$$

Since the Rs cancel out, what is left is the following:

$$\gamma \Delta r_{it} = \frac{\partial Q}{\partial R} \frac{\Delta R_{it}}{Q_{it}}$$

Assuming a depreciation rate of zero for R&D investment (assuming a long patent protection which would protect R&D findings and reduce depreciation), $\frac{\Delta R_{it}}{Q_{it}}$ can be replaced with one year's R&D investment. Therefore we arrive at the following:

 $\gamma \Delta r_{it} = \psi \frac{R_{it}}{Q_{it}}$ where ψ is the rate of return on R&D investment and RD_t is one year's R&D investment.

As a result in the estimation equation, R&D capital stock is replaced by the R&D intensity:

$$\Delta(q_{it}-l_{it}) = \lambda + \Delta a_{it} + \alpha \Delta(k_{it}-l_{it}) + \psi \, R_{it}/Q_{it} + \theta \, \Delta l_{it} + v_{it}$$

Even though this approach enables one to avoid calculating the R&D capital stock, it is not free from problems of its own. For one thing, the coefficients that will be estimated are gross rates of return and in order to reach the net rate of return one still needs to estimate the depreciation rate. Kinoshita (2001) Secondly, here the rate of return or marginal productivity is assumed to be constant and the elasticity is assumed to vary due to the ceteris paribus nature of econometric estimation whereas the reverse is assumed when the estimation is performed with the capital stock variables and elasticities. (Griliches and Mairesse 1985). However, although conceptually it seems more reasonable to assume the rate of returns as constant and to derive the elasticities, the estimated rates of return in the literature have turned out to be variable owing to the uncertainty of the R&D output. Hall et.al. (2010) attribute this to the fact that before carrying out an investment, firms face ex ante expected returns which are equal to cost of capital but, what the researchers measure are the ex post returns. Thus the variance in the supposedly constant rates of returns emerges.

1.5 Spillovers

The rival and partially excludable nature of knowledge yields it an easily transmittable item between people and firms. Owing to poor patent protection, or difficulty to keep innovations secret, reverse engineering, benefits from R&D can not be kept to the innovating firm. The higher the codification of knowledge becomes, the easier it gets for other firms with absorptive capacity to benefit from that knowledge. This generates a knowledge pool in the industry. According to Griliches (1979) there are two types of spillovers: rent spillovers and true knowledge spillovers. Rent spillovers are knowledge spillovers enjoyed by a firm as it purchases new products or services from other industries, makes direct investment, hires workers, collaborates with research partners or gets engaged in mergers and acquisitions. Hall et al (2010). On the other hand true spillovers are `ideas borrowed by the research teams of industry i from the research results of industry j' (Griliches, 1979 p.104). Although conceptually it is easy to distinguish these spillovers from one another empirically it is quite difficult to separate them. Mohnen (1996). Mainly two approaches are used for modeling spillovers: one of them sums up all R&D expenditures of firms and the other locates firms into a patent space. The approach based on summing up R&D expenditures using input output matrices (Wakelin, 2001, Aiello and Cardamone 2005) is regarded more likely to be a better indicator of rent spillovers. On the other hand the approach making use of proximity based on patent space (Los and Verspagen 2000, Cincera 2005) is thought to be more appropriate for knowledge spillovers. (Wieser 2005)

There are a number of studies focusing on the significance of these spillovers in the literature, for instance Los and Verspagen (2000), Griffith et. al (2006) ,Aiello Cardamone (2008) found the social knowledge pool had a positive impact on firm's performance.

1.6 Selection bias, Multicollinearity and Endogeneity

An important issue that has not been addressed until 1998 is the issue of selection bias. While studying the impact of R&D on productivity, most researchers only used data belonging to R&D performers, i.e (Dillig-Hansen et.al 1999, Aldieri et. al. 2008). In a seminal paper Crepon, Duguet and Mairesse (1998), connected three different strands of R&D research in one study. Via three equations they addressed the selection bias issue and the simultaneity problem and connected R&D, innovation and productivity together. To account for a firm's research behavior they first use a tobit model, then in the second

equation they studied the determinants of innovation, one of which is R&D investment. Finally, in the last equation they scrutinized the impact of innovation on productivity. After their paper, researchers have started to use models such as Heckman two stage procedure or probit or tobit to deal with the selection bias. (Loof and Heshmati 2002, Damijan et al. 2003, Aiello and Cardamone 2008, Loof (2009), Banri et.al (2010), Vakhitova and Pavlenko 2010).

In addition to the above problems Griliches (1979) points to two other econometric problems regarding the impact of R&D on productivity: Multicollinearity and endogeneity. He claims multicollinearity arises because most of the variables used in the regressions turn out to be highly collinear with one another. However, he also points out that when data is at the firm level, this problem does not matter much. On the other hand, he underlines the causality issue between productivity and R&D investment. As output depends on past R&D investment, on another front, past R&D investment also depends on previous productivity and profitability. Furthermore current R&D depends on the expectation of productivity and profitability in the future. To deal with this problem of simultaneity Griliches (1979) recommends the use of recursive equation systems.

1.7 Rate of Return and Elasticity Estimates

Wieser (2005) reports that estimates of the rate of return to R&D range from 7% to 69% while estimates of elasticity of output with respect to R&D range between 0,03-0,38. The wide range of these figures are attributed to the double counting. Also the wide difference between these estimates has been found to arise due to the regression technique used. Hall and Mairesse(1995) in Wieser (2005) state that

"The pattern of estimates usually yields an R&D capital elasticity in the cross section dimension which is statistically significant, usually large and even possibly of the same order of magnitude as the elasticity of ordinary capital, whereas the estimates in the time dimension, which control for permanent differences across firms, whether within, long-differenced or first-differenced, typically have an R&D capital elasticity which is much smaller about one third or half that of ordinary capital, and often statistically insignificant" Mairesse and Sassenou (1991) state that time series estimates are more reliable than cross section estimates because time series estimates do not suffer from omitted firm specific variable biases whereas this is a problem present in cross sectional studies.

3. Hypotheses

R&D is expected to affect labor productivity positively. R&D indicates private knowledge of firms. Thus firms with unique knowledge acquired through R&D efforts are expected to have higher productivity. However R&D also has a social side. Firms may benefit from knowledge spillovers from other firms'. (Griliches 1979) Therefore the private and social aspects of R&D should be taken into account together. As far as the spillover effect is concerned the literature claims that particularly foreign firms constitute a major source of knowledge.(Damijan et. al 2003). The larger the presence of R&D activities of foreign

firms in a host country, the higher is the productivity of domestic firms. This is due to knowledge spillovers from the foreign firms. However when foreign firms enter a market, they also bring competition (Kemme et.al. 2009) and due to this competition effect, domestic firms' productivity can be negatively affected. (Aitken and Harrison 1999) Which one of these two opposing forces will override the other can not be foretold. Therefore we do not have a specific expectation regarding the spillover effect on labor productivity growth.

4. The Empirical Model

Following the literature we take an augmented Cobb Douglas production function as in the following:

$$Q_{it} = Ae^{\lambda t} K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma} e^{\varepsilon_{it}}$$

where

Q=output,
A= impact of external factors
K=physical capital stock
L= labor
R= R&D capital stock

 λ is the rate of disembodied technical change, α, β, γ are elasticities with respect to physical capital, labor and knowledge capital and t is the time index. ε_{it} includes any errors in the specification. The physical capital and knowledge capital stocks are generated via the perpetual inventory method.

$$K_{t} = I_{t} + (1 - \delta)I_{t-1} + (1 - \delta)^{2}I_{t-2} + \dots = I_{t} + (1 - \delta)K_{t-1}$$

Where K represents the capital stock, d stands for the depreciation rate and I represents the annual investment. The initial capital stock is calculated assuming there is permanent growth at the rate of depreciation. After the generation of the physical and knowledge capital stocks with the perpetual inventory method, we plug these into the production function and take logs which yield the following:

$$\ln Q_{it} = \ln A_{it} + \lambda_t + \alpha \ln K_{it} + \beta \ln L i_t + \gamma \ln R_{it} + \varepsilon_{it}$$

In order to get the labor productivity form, we subtract l and subtract and add αl and γl to both sides, to get

$$q_{it} - l_{it} = a_{it} + \lambda_t + \alpha k_{it} + \alpha l_{it} - \alpha l_{it} + \gamma r_{it} + \gamma l_{it} - \gamma l_{it} + \beta l_{it} - l_{it} + \nu_{it}$$

where v_{it} = In(ε_{it}).After rearranging the common terms we arrive at

$$(q_{it} - l_{it}) = \lambda_i + a_{it} + \alpha(k_{it} - l_{it}) + \gamma(r_{it} - l_{it}) + (\alpha + \beta + \gamma - 1)l_{it} + v_{it}$$

Here by allowing $\theta = \alpha + \beta + \gamma$ we rephrase the labor productivity equation to be able to test the assumption of constant returns to scale. Thus we have

$$(q_{it} - l_{it}) = \lambda_t + a_{it} + \alpha(k_{it} - l_{it}) + \gamma(r_{it} - l_{it}) + (\theta - 1)l_{it} + v_{it}$$

Assuming a_{it} represents the impact of external factors which are knowledge spillover from foreign firms in the industry, knowledge spillover from domestic firms in the industry, exporting, foreign ownership and technology transfer, we get the estimation equation:

$$(q_{it} - l_{it}) = \eta_i + \lambda_t + \alpha(k_{it} - l_{it}) + \gamma(r_{it} - l_{it}) + (\theta - 1)l_{it} + f_{it} + sf_{it} + sd_{it} + b_{it} + x_{it} + d_i + v_{it}$$

where

f_{it}= foreign ownership dummy with shares of 10% and more.

sf_{it} = natural logarithm of RD knowledge pool of foreign firms in the industry

sd_{it} = natural logarithm of RD knowledge pool of domestic firms in the industry

b_{it}= dummy for firms transferring technology

x_{it}= dummy for exporting firms

d_i= Industry dummies

 η_i = firm specific effects

Following Hall and Mairesse (1992), instead of λ_i which represents the disembodied technical change, we use time dummies because we believe the effect of disembodied technical change may change from one year to another.

Foreign ownership's effect on productivity is twofold. When a parent firm decides to invest in another country, its expectation on that investment must be higher than average return elsewhere. Therefore the expectation in the literature is that foreign ownership should produce positive effect on productivity. Yet, the empirical evidence is mixed. While there are positive significant effects (Damijan et al 2003), negative effects (Dillig-Hansen et al 1999) and insignificant effects (Chudnovsky et. al. 2006) are cited as well.

The R&D spillover variable which is composed of the sum of the R&D expenditures from other firms in the industry is expected to have a positive effect on productivity. Considering the time it takes for knowledge to travel within the industry, this variable is lagged by one year. While in developing economies insignificant or even negative horizontal spillovers are detected (Aitken and Harrison, 1999, Kinoshita 2000, Damijan *et al.* 2003,), positive spillovers are found in developed countries. (Haskel *et al.* 2007).

The inclusion of a license dummy serves the purpose of tracking the effect of technology transfer. Firms in developing countries may choose to purchase technology rather than performing R&D on their own. Therefore technology transfer could have a positive effect on productivity. In the literature positive significant effects of technology transfer on productivity are found. (Dillig-Hansen et. al. 1999, Banri et al (2001).

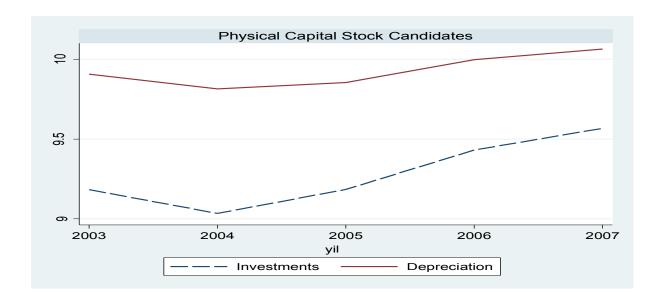
Firms that export have to survive tough competition abroad. While exporting they also have the opportunity to see advanced technologies and learn from them. Thus exporting could be an incentive to increase productivity. (Vahter, 2010) The motive for including an export dummy is to see if there is a positive effect of exporting on productivity. While there are researchers finding positive effects of exporting on productivity (Luintel et al. 2010), others find negative significant impact too. (Kathuria 1998)

5. Data Cleaning and Variables

The Structural Business Survey (SBS) from Turkish Institute of Statistics (TIS) is used in this study. SBS is an enterprise level survey. We start out the analysis with 92456 observations for the period 2003 to 2007. Eliminating the nonmanufacturing firms leaves us with 48.983 observations. We need to drop the firms with less than 20 employees because TIS does not visit every single small firm with less than 20 employees. That leaves 45.418 observations in the sample. Next to make sure we have five consecutive years of data for the firms in the analysis, we drop the firms that have missing data for 2003- 2007. This costs us 8971 observations. Next, taking care of the false entries such as export intensity figures larger than 1 and outliers that are detected via scatter plots, we lose 867 observations which leaves us with a sample of 35580 observations. However as we will be using only R&D conducting firms, this restriction reduces the sample size considerably. The number of observations for R&D conductors for the 2003-2007 period happens to be 5393.

To compute the labor productivity variable we use the natural logarithm of the ratio of value added to labor. Value added is defined as the difference between output, raw material costs and energy costs. It is deflated by wholesale price index at the two digit NACE level.

To determine the physical capital stock variable we use two different candidates. The investment flows and the annual depreciation. Both of these variables are first deflated by capital deflators at the two digit level. Next we interpolate the depreciation variable assuming any firm that has sales revenue in a year must have a positive depreciation value. However we do not interpolate the investment variable as we can not make the same assumption for investment flows, because a firm may not necessarily have positive investment flow every single year. Despite interpolation, there are still a lot of missing values in the two variables so among the two we pick the depreciation variable to use in the calculation of our physical capital stock since it has less missing values (2490 versus 10659). Following Taymaz et. al (2008), we use a depreciation rate of 6.7% in the physical capital stock calculation.



However for the R&D stock we use a depreciation rate of 25%. Although other depreciation rates have been used in the literature, as indicated in the literature the value of this rate does not matter much as far as the computation of the capital stock is concerned. (Hall. et. al 2010) R&D expenditures are deflated by the wholesale price index. Table 1 lists the variable definitions and Table 2 presents the summary statistics.

Table 1: Variable Definitions

Labor Productivity	Ln (value added _t / employment _t)
Physical capital stock intensity	Ln (Depreciation _t / employment _t)
Employment	Ln (Number of employees) t
R&D stock intensity	Ln(R&D stock _t / employment _t)
Foreign Ownership	Dummy for firms with more than 10% of capital owned by foreign firms
Foreign Knowledge Spillover in the industry	Ln(Sum of foreign RD in the sector-the firm's RD+1) _{t-1} *
Domestic Knowledge spillover in the industry	Ln(Sum of domestic RD in the sector minus-the firm's RD+1) _{t-1}
Export dummy	Dummy for those who export

Technology Transfer	Dummy for those who use licensed technology			

 $^{^*}$ 1 is added to get rid of the zeros.

Table 2: Summary Statistics for R&D Performers

		standard	number of
	mean	deviation	observations
Labor productivity	10.3667	0.9918	5269
Physical capital stock intensity	10.5308	1.5657	5199
Employment	7.8307	1.4879	3791
R&D stock intensity	4.8571	1.2061	5393
Foreign ownership	0.0984	0.2979	5393
Foreign knowledge spillover in the industry	6.6245	7.0167	5393
Domestic knowledge spillover in the industry	14.3611	1.8339	4690
Export dummy	0.7695	0.4212	5393
Technology transfer	0.2014	0.4011	5393

6. Methodology

In the productivity equation since we use natural logarithms of R&D capital stock, those firms that do not engage in R&D automatically drop out of the equation. This introduces a selection bias to the sample that we use. To be able to keep those firms that do not conduct R&D in the sample, we make use of the Heckman procedure. In Heckman procedure, the bias that arises due to using non random sample is tackled as a specification bias emerging due to omitted variable problem. Heckman (1979). Heckman suggests the use of estimated values of the omitted variables as explanatory variables in the model. Therefore before running the productivity regression, first we estimate a probability that a firm's productivity is conditional on its R&D performing behavior.

 $\Pr(p_{it} = 1 \mid X_{i,jt_o}) = S(X_{it} \neq X_{jt})$ where i and j indicate the R&D performers and non performers respectively. The error terms are assumed to be IID and normally distributed. S(.) is the cumulative distribution function of the normal distribution function. X is a matrix of firms' determinants to conduct R&D. As determinants of R&D we use the average wage rate, foreign ownership indicator, backward and forward spillovers, capital intensity, number of employees, export intensity, Herfindahl index, R&D spillover from foreign firms in the sector and R&D spillover from foreign firms in the province.

Next we calculate the Inverse Mill's Ratios (IMR) for each year from 2003 to 2007. Then in order to be able to use the IMR as an explanatory variable in the panel data regressions we append the cross sectional estimates one underneath the other. This is a technique advised by Wooldridge (2002) to deal with selection bias in the panel data framework.

Another way to approach the selection bias problem in panel data could be the use of a panel probit regression to generate the predicted probability of each firm to undertake R&D and then to compute the IMR based on the predicted probabilities. However, the problem with this technique is that with panel data, probit can be estimated only with random effects. This excludes the choice of a fixed effects regression at the second stage. As the aim here is to conduct both fixed and random effects approaches along with others to deal with endogeneity, the technique recommended by Wooldridge (2002) is preferred in this context.

Initially fixed effects and random effects models are estimated. Fixed effects deals with firm heterogeneity by transforming the data in a way that leaves all the unobserved characteristics such as management differences. The downside of fixed effects is the fact that it takes only the variation in the time dimension and disregards the one in the cross sectional. As our time dimension spans only 5 years, and as R&D investment is not an easily changing investment in time (Cincera Ravet 2008), fixed effects may have a hard time trying to analyze the variation of R&D stock. Poor results coming out of fixed effects estimation is not an uncommon finding as reported in the literature. Rather low fixed effects coefficient estimates or even insignificant estimates are reported by numerous studies. (Griliches and Mairesse 1984, Los and Verspagen 2000, Hall et. al. 2010) On the other hand random effects seem more likely to capture the cross sectional variation across the firms , but then again with random effects there is the assumption of no correlation of the error term with the explanatory variables or no omitted variable bias which may not hold as well.

Furthermore, since R&D is claimed to be an endogenous variable with respect to productivity, (Arvanitis Sturm 2008, Bednarek 2010, Parisi et. al 2006) a technique that deals with endogeneity is called for. The preferred method is system GMM (Hall and Mairesse 1995, Griffith et al. 2006) instead of the IV methodology as it is very difficult to find appropriate instruments for capital, R&D stock and labor letting alone the other explanatory variables. Furthermore Hall and Mairesse (1996) report that with system GMM the standard errors are much smaller as opposed to the ones obtained with IV estimation because system GMM uses more regressors than IV does. An important issue with system GMM is the determination of the endogenous, predetermined and exogenous variables. A review of the literature reveals that most researchers take physical capital, knowledge capital and labor as endogenous (Okada 2005, Aldieri et. al 2008), others take all firm level variables as endogenous (Griffith et. al 2006).On the other hand spillover variables are taken as exogenous because they are generated at the industry level and the assumption is the no single firm can affect the industry on its own.(Aiello and Cardamone 2008)

7. Estimation Results

Initally we run cross sectional probit estimations for each year from 2003 to 2007. From these probit regressions, we compute IMR for each year again. Then we generate one IMR for the panel data from these cross sectional predictions and use that in the productivity regressions.³ Table 3 reports the results of the fixed and random effects regressions with the IMR variable produced in the prior regressions.

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³ As there are five cross sectional regressions we do not report the results here. However they can be provided by the authors upon request.

Table 3: Fixed and Random Effects Regressions

VARIABLES	Fixed Effects	Random Effects
Physical capital stock intensity	-0.0244	0.167***
	(0.0487)	(0.0188)
R&D stock intensity	0.0277	0.114***
	(0.0458)	(0.0189)
Returns to scale	-0.492***	-0.148***
	(0.0990)	(0.0278)
Foreign ownership	0.0273	0.203***
	(0.110)	(0.0640)
Lagged Knowledge spillover from foreign firms	-0.000814	-0.00382
	(0.00267)	(0.00249)
Lagged Knowledge spillover from domestic firms	0.0181	-0.00760
	(0.0293)	(0.0148)
Exporting	0.0367	-0.00341
	(0.0491)	(0.0400)
Technology Transfer	-0.0420	-0.0193
	(0.0443)	(0.0365)
IMR	-0.520***	-1.019***
	(0.109)	(0.0844)
Constant	13.57***	10.18***
	(1.083)	(0.504)
Observations	2136	2136
R-squared	0.077	
Number of firms	766	766
P value of the Hausman statistic	0.0000	

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Two digit industry dummies and time dummies included.

In the first column of Table 3 where the fixed effects results are presented, only two variables are significant, the returns to scale and the IMR. The Hausman test favors the results of the fixed effects regression; therefore we do not discuss the results from the random effects regression, although a number of variables emerge as significant there. In this estimation, all firms, whether they are in high technology, medium technology or low technology is included. To differentiate industrial differences we employ two digit (NACE) industry dummies again. However in the literature, it is stated that high and medium technology sectors have a better chance than low technology sectors in terms of conducting R&D and observing the effects on productivity.(Kemme et. al 2009) In our case, the ratio of low technology firms to all firms conducting R&D is not low. In Table 4 we see that on the average the ratio of low technology firms to all R&D performers change between 0.28 and 0.37. Therefore it makes sense to consider only the high and medium technology firms to see the impact of R&D on productivity. In table 5 we include only the high and medium technology firms in the regressions.

Table 4	Ratio of	Low Tech	firms to all F	R&D perform	ning firms	
Number of low tech firms		458	419	425	288	214
Number of high and medium tech fi	rms	769	814	806	655	545
		1227	1233	1231	943	759
Ratio of Low tech firms to a	II R&D					
performers		0.37	0.34	0.35	0.31	0.28

Table 5: Fixed and Random Effects results for High and Medium Technology Firms Only

VARIABLES	Fixed Effects	Random Effects
Physical capital stock intensity	-0.0170	0.175***
	(0.0553)	(0.0196)
R&D stock intensity	-0.0187	0.118***
	(0.0527)	(0.0216)
Returns to scale	-0.554***	-0.139***
	(0.108)	(0.0304)
Foreign ownership	0.0729	0.211***
	(0.137)	(0.0702)
Lagged Knowledge spillover from foreign firms	-0.00332	-0.00494*
	(0.00330)	(0.00290)
Lagged Knowledge spillover from domestic firms	0.0201	-0.00183
	(0.0402)	(0.0156)
Exporting	0.00231	-0.0401
	(0.0560)	(0.0432)
Technology transfer	-0.0607	-0.0271
	(0.0490)	(0.0395)
IMR	-0.495***	-0.980***
	(0.121)	(0.0913)
Constant	13.93***	0
	(1.233)	(0)
Observations	1567	1567
R-squared	0.075	
Number of firm	546	546
P value of the Hausman statistic	0.1870	

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Two digit industry dummies and time dummies included

When only the high and medium technology firms are included in the estimation, the Hausman test favors the results of the random effects regression. In the literature most of the time fixed effects results are reported, however, there are studies that prefer the random effects results over the fixed

effects ones. (Ortega-Argiles et. al 2009) In Table 3, both the fixed and the random effects results are listed. In the first column where fixed effects results are presented, none of the coefficients turn out significant except for returns to scale and IMR. However in the second column, the random effects results indicate that physical capital stock, R&D capital stock and foreign ownership variables all have highly significant coefficients at 1% level. The knowledge spillover variable from foreign firms has a negative coefficient which is significant at the 10% level. Returns to scale and IMR are also highly significant but their signs are negative. The elasticity of R&D capital stock at 0.118 is in line with those in the literature. In a literature review article Wieser 2005 reports R&D elasticities are found in the range from 0.03 to 0.38.

Physical capital stock also has a highly significant positive impact on labor productivity. As a matter of fact the elasticity of physical capital stock is higher than the elasticity of R&D capital stock. However, in terms of magnitude, foreign ownership has the highest impact on labor productivity. Hence, ceteris paribus, foreign firms with a controlling interest of 10% or higher have 20% higher productivity than domestic ones. This is a result also supported by the literature. (Kemme et.al. 2009)

The negative knowledge spillover from foreign firms is a surprising result as one expects this variable to have a positive effect. However, as Aitken and Harrison 99 suggest this variable may be capturing the market stealing effect of foreign firms. Since foreign firms also bring along competition, this effect may dominate the positive knowledge spillover effect. Particularly inefficient domestic firms may lose market share to the foreign firms and this may be reflected in their productivity. (Kemme et.al. 2009)

The significantly negative returns to scale variable is an outcome that has been found in the literature as well. (Griliches and Mairesse 1984, Los and Verspagen 2000, Cincera and Ravet 2010) One reason for this result is stated as measurement errors in the labor and capital variables, while another one is simultaneity.

Even though the fixed effects results are not favored by the Hausman test, if we compare the differences between the fixed effects and random effects coefficients, we see that the random effects coefficients are higher than their fixed effects counterparts. This is a situation that has been frequently reported in the literature. Mairesse and Sassenou (1991) and Griliches and Mairesse (1984) report that time series results are much smaller or even insignificant than the results of the cross section regressions. They claim this may be attributable to collinearity of R&D and physical capital stock in time. However, once again simultaneity of independent variables and productivity emerges as another problem causing the discrepancy between fixed and random effects estimates. To address the simultaneity bias, one of the proposed methodologies is application of system GMM technique, which is what is presented in table 6.

Table 6: System GMM result.

VARIABLES

Physical capital stock intensity	0.0723
	(0.0644)
R&D stock intensity	0.177**
	(0.0868)
Returns to scale	-0.268
	(0.219)
Knowledge spillover from foreign firms	-0.0141*
	(0.00833)
Knowledge spillover from domestic firms	0.00767
	(0.0247)
Exporting	-0.0106
	(0.237)
Technology transfer	0.365*
	(0.208)
IMR	-1.843**
	(0.877)
Constant	11.91***
	(2.860)
Observations	3233
Number of firms	739
P value of second degree autocorrelation test	0.325
P value of the Hansen test	0.355
Robust standard errors in narentheses	-

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Two digit industry dummies and year dummies included.

In the system GMM application, one important factor to consider is the use of healthy lags as instruments. However, if there are many missing values in the data as is the case with our R&D capital stock variable, one suffers from poor instruments and autocorrelation of degree two problems. In order to deal with this issue, following the literature (Griffith and Webster 2004), we impute the R&D capital stock variable with its previous lag. Then again following the literature we assume physical and R&D capital stocks and labor as endogenous (Okada 2005, Aldieri et. al 2008, Griffith et. al 2006). We also take foreign ownership as endogenous since foreign firms are claimed to acquire highly productivity firms in the first place. (Dillig-Hansen et. al 1999, Kemme et. al 2009) Exporting firms and technology transferring firms also are found to have higher productivity and in return their productivity impacts higher exports and increased use of licensing (Wei and Liu 2006, Loof 2009). Therefore both exporting and technology transfer variables are taken as endogenous. As far as the spillovers are concerned, we follow the literature to assume they are strictly exogenous because these are industry level variables and firms can not be large enough to affect the industry on their own.(Aiello and Cardamone 2008)

When we interpret the system GMM results in Table 6, we pay attention to two tests in particular. The second degree autocorrelation test and the Hansen test. The null hypothesis in the autocorrelation test is there is no autocorrelation and the null of the Hansen test is that the instruments are valid. Therefore in order to pass these tests, one has to have high p values. In our case, as presented in Table 6, our results are free from both second degree autocorrelation and poor instruments problem. The system GMM application reveals in Table 6 that capital stock and R&D capital stock have positive and significant effects on labor productivity. The R&D elasticity however increases to 0.177 which is larger than 0.118 in the random effects regression disregarding the simultaneity bias. The magnitude of the capital stock variable falls to 0.07, and loses its significance. Spillovers from foreign R&D performers have a significantly negative effect on labor productivity. This variable may be capturing the 'market stealing' effect of foreign firms in the market because foreign firms' market share increase causes a decrease in domestic ones, which shows as their output decreases. Such a fall in output is translated into lower productivity. However as the technology transfer variable indicates, those firms that use license also have higher labor productivity and this is a significant effect. Another significant effect is the one with the IMR. The significance of IMR indicates that there is indeed a selection bias that needs to be accounted for while studying the impact of R&D on productivity.

8. Conclusion

In this paper we study the impact of R&D on labor productivity in Turkey. To that end, we make use of a framework most of the firm level literature prefers, an extended Cobb Douglas production function. Making use of the Structural Business Survey from the Turkish Institute of Statistics, we use firm level data that spans a five year period from 2003 to 2007.

Our estimates of R&D capital stock elasticity yields 0.18, which falls within the range of 0.03 to 0.38 as stated by Wieser (2005). However in addition to R&D capital, technology transfer emerges as another factor that has a significant positive impact on labor productivity. On the other hand, we find a negative spillover effect from the knowledge pool of foreign R&D performers in the industry. This could be attributable to a competition effect observed in the presence of foreign firms. When one studies the impact of R&D capital on productivity, naturally, one takes into account only R&D conducting firms. However as our results indicate, it is imperative take into account the non-random sample by applying methods that address selection bias.

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