R&D SUPPORT, INNOVATION AND EMPLOYMENT GENERATION: THE TURKISH EXPERIENCE

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ABSTRACT

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This thesis assesses how technology policy, R&D activities and innovativeness interact to yield higher economic performance in Turkish manufacturing industries. The first aim of this thesis is to analyze the role of R&D support programs as one of the instruments of technology policy on the demand for researchers. We evaluated the impact of R&D support receiving on the demand for researchers by estimating a two stage treatment effect model that solves the problem of selection bias and found that receiving R&D support encourages firms to demand more researchers. The second aim of this thesis is to analyze the determinants of generating product and process innovations. We evaluated the determinants of generating product and process innovations by estimating a bivariate probit model and found that the determinants of generating product and process innovations were related but they varied with the technological level and opportunity of the industry. The last aim of this thesis is to analyze the effect of product and process innovations on employment. We hypothesized that these two types of innovations have different impacts on employment and test this hypothesis by estimating two different econometric models: the first one is a treatment effect model controlling for the endogeneity of innovations and the second one is a selection model that controls for survival status of the firm. We found that the impact of product innovations on the employment growth rate is negative and the impact of process innovations on the employment growth rate is positive regardless of technology level of industries.

Keywords: R&D support, labor demand, product and process innovations, employment generation

ÖZ

AR-GE DESTEĞİ, YENİLİK VE İSTİHDAM OLUŞUMU: TÜRKİYE DENEYİMİ

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Bu tez teknoloji politikasının, AR-GE faaliyetlerinin ve yeniliğin Türk İmalat Sanayiinde daha yüksek ekonomik performans oluşturmak için nasıl etkileştiğini değerlendirmektedir. Bu tezin ilk amacı, teknoloji politika araçlarından biri olan AR-GE destek programlarının araştırmacı talebi üzerindeki etkisini araştırmaktır. AR-GE desteği almanın araştırmacı talebi üzerindeki etkisi seçim yanlılığı sorununu çözen iki kademeli "davranış etkisi" (treatment effect) modeli tahmin edilerek değerlendirilmiş ve AR-GE desteği almanın firmaların araştırmacı talebini artırmayı teşvik ettiği bulunmuştur. Bu tezin ikinci amacı, ürün ve süreç yeniliğini belirleyen faktörleri analiz etmektir. Ürün ve süreç yeniliğini belirleyen faktörler "iki değişkenli probit" (bivariate probit) modeli tahmin edilerek değerlendirilmiş ve sonuç olarak ürün ve süreç yeniliğini belirleyen faktörlerin birbirleriyle ilgili oldukları fakat sanayinin teknolijik seviyesi ve olanaklarıyla farklılaştıkları bulunmuştur. Bu tezin son amacı, ürün ve süreç yeniliğinin istihdam üzerindeki etkilerini incelemektir. Bu iki tür yeniliğin istihdam üzerinde farklı etkileri olduğunu varsayarak, bu varsayımı iki farklı ekonometrik model kullanarak tahmin ettik. Birinci model yeniliğin dışsallığını kontrol eden "davranış etkisi" tahmin yöntemidir ve ikinci model firmaların kapanmamış olmalarını kontrol eden bir "seçim" (selection) modelidir. Sanayilerin teknolojik eğilimleri gözetilmeksizin ürün yeniliğinin istihdam üzerindeki etkisi olumsuz ve süreç yeniliğinin istihdam üzerindeki etkisi olumlu olarak bulunmuştur.

Anahtar Kelimeler: AR-GE desteği, isgücü talebi, ürün ve süreç yeniliği, isthidam oluşumu

To my parents

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CHAPTER I

INTRODUCTION

The central premise of studies on development economics is to explore the diversity of the outcomes of the development processes. At the core of these studies lies the emphasis on structural change and the connection between this and technological and institutional change. The fact that development for each economy has its own idiosyncratic characteristics puts forward the claim that the connection between technology and development is itself a rather complex phenomenon combining adaptation, selection, diversity and creation.

The key to understand the role of technology in this complex and dynamic system lies in exploring the interaction between the creation, usage and acquisition of technological knowledge and market processes combining knowledge of technology with the knowledge of firms. Economic peculiarities relating to production and diffusion of knowledge like indivisibilities, uncertainty, lack of appropriability and externalities, interact and develop in different ways to produce market failure and social inadequacy of private incentive mechanism in development of technology. Market failures in relation to knowledge production and innovation in terms of imperfect appropriation of returns and uncertainty outline the policy recommendation that such socially beneficial knowledge generation should be publicly provided or subsidized via building necessary infrastructure and institutions.

The basic economic justification for technology policy and more particularly R&D supports is linked to the issue of market failure. Due to imperfect appropriability of innovations or spillover effects, the social rate of return to research activities implemented by firms is higher than the private rate of return. Indeed, the optimal amount of R&D is theoretically reached when the marginal social cost is equal to the marginal social benefit. This central argument justifies

government support to private R&D by offering incentives to alleviate this market failure in the allocation of resources devoted to technological activities. R&D supports is one of the main policy tools at government's disposal that link the internal efforts of firms with public funding stimulus.

As promoting the generation and diffusion of technological change has become an important goal of public intervention in most of the countries, the fraction of real gross national product being directed by public agencies toward private R&D funding increased gradually. The increasing budget allocated to pubic R&D support programs acknowledged the need for analyses evaluating the relationship between R&D support programs and its effects on output growth, productivity and on R&D intensity.

The literature on technology policy has emphasized the importance of R&D support programs as an instrument to affect the rate and direction of technological change. There are a large number of empirical studies that assess the effects of R&D support programs on technological activities and a robust finding of these studies is the stylized fact that R&D support-receiving firms increase their expenditures on R&D activities. This increase in R&D expenditures through publicly subsidized R&D fosters innovativeness and this increase in innovativeness in turn causes firm growth which on the aggregate level results in growing economic performance and also in increasing the firms' demand for labor. Although the literature provided the insights into the R&D support having stimulating impacts on private R&D expenditures and on output growth, little research has tended to focus on the relationship between employment generation and R&D supports.

The first aim of this thesis is to analyze the role of R&D support programs in Turkey as one of the instruments of technology policy on the demand for researchers over the period 1993-2001. We hypothesize that receiving R&D support encourages firms to demand more researchers and test this hypothesis by estimating a two stage treatment effect model that solves the problem of selection bias and hence endogeneity of R&D support receiving. We first estimate the probability of receiving R&D support by using firm size, firm's status of transferring technology, share of skilled employees, lagged R&D intensity, sectoral R&D intensity, measures of spillover and previous support receiving status as

explanatory variables. We then estimated static and dynamic labor demand specifications for researchers by treating the receipt of R&D support as endogenous and by using wage rate of researchers, other prices like input, capital and average wage rate of all employees and also by including a measure of technological capability of firm- technology transfer- as explanatory variables.

Analysis of technology policy aimed at supporting and encouraging technological development through R&D can only provide a part, though a very important part, of the picture. As Metcalfe (1995) states, the economics of technology involves much more than the analysis of R&D activity. Private profit-seeking firms will allocate resources to conducting R&D if they believe in the existence of some unexploited technical opportunities and if they anticipate some economic benefit deriving from the introduction of innovations (Dosi, 1988: 1120). Exploring R&D support programs as a tool of technology policy affecting the allocation of resources devoted to R&D will make it possible to analyze the effects of these public funding mechanisms on R&D activity. This stimulated R&D activity on the other hand contributes to firm performance in increasing the probability of innovative outcome that is another part of the picture necessitating a further elaboration.

It is often claimed that innovation is one of the main factors underlying a country's international competitiveness, economic growth rate and performance. Neoclassical economics has long ignored the role of innovation in economic change but since mid 1980s, the new growth theory has started to perceive innovation as an engine of growth. The intuition that technological progress was a key determinant of sustained economic growth provided the impetus of a large body of empirical literature that focused on understanding the processes and determinants of innovation within and between firms, industries and countries.

The process of innovation embodies complex and varying relations between forms and creation of knowledge, and includes different combinations of opportunities of innovation, firm based capabilities to acquire these opportunities and economic incentives to do so based on market conditions (Dosi, 1988:1147). Moreover, these specific opportunities and mechanisms that are developed also evolve creating heterogeneity and differences in innovativeness at firm and sector level. It has become a common practice in the literature to analyze innovation as a

highly differentiated process that is specific in its scope depending on the strategies pursued by firms and industries. The theoretical distinction between the development of process and product innovations further leads the way to evaluate potential differences in the determinants of introducing them.

Potential differences in the presence and intensity of innovative efforts in firms and industries have received a lot of attention in the economic literature and most of this research tries to expand the line opened by Schumpeter suggesting the distinct role of large firms possessing some degree of market power is suited for the introduction of new products, production processes and management methods in an economic system. The previous empirical literature that has a narrower concern has focused on attributes of firms that are mostly related to innovativeness like firm size and market structure. As empirical results bearing on these attributes are inconclusive, there become a new growing literature engaging to understand the inter-industry differences in innovation by incorporating the structure of demand, the nature and abundance of technological opportunity and the conditions governing appropriability of the returns from innovation into the study of innovation.

The second aim of this thesis is to analyze the determinants of generating product and process innovations in Turkish manufacturing industries over the periods 1995-1997 and 1998-2000. We evaluated the determinants of generating product and process innovations by estimating a bivariate probit model including both product and process innovations simultaneously. We utilize several measures of firm and industry specific characteristics such as firm size and age and concentration ratio as explanatory variables to test traditional Schumpeterian hypothesis. Going one step further, we also introduce technology specific characteristics like technology transfer, share of skilled employees, R&D intensity and internet usage intensity to check for inter industry differences governing technological opportunity and appropriability conditions. In addition, we incorporate R&D support receiving status into the traditional modeling of the determinants of introducing product and process innovations in order to check for stimulating effects of public R&D funding on innovativeness.

There are three distinct phases in the process of technological change that should be clarified before taking one step further. The first distinct phase is the

creation of new idea that has the potential to be applied in the economy. The analysis regarding the evaluation of the effects of R&D support on R&D activities through its impact on demand for researchers provides insights into this first phase. The second phase is the first commercial application of invention that is innovation. We explore this second phase by analyzing the determinants of generating product and process innovations through investigating technological and economic conditions in which the innovator operates. This analysis sheds light on the necessity of evaluating the third phase, imitation, that is referred as the diffusion of the innovation to other firms and sectors. This last phase of technological change is assessed in this thesis because the economic impact of an innovation is observed in this phase in which the technology is now used in many places.

The application of inventions and design of new products and processes by firms is seen crucial to the survival and success of firms as it alters the production costs, market competitiveness and hence economic performance of innovative firms. The employment consequence of such technological activity is often regarded as having mixed outcomes: improvements in product design mainly affecting the demand for product, will have a positive effect on the market share of the firm that innovates and thus on its employment. However, the adoption of new process technology mainly affecting the cost structure and hence the supply of product is frequently labor saving due to the increase in the productivity of labor generating a reduction in labor demand. These two divergent outcomes have led economist and policy makers to debate the economic and social consequences of technological change on labor market. Therefore, the answer to classical question "*Does technology creates or destroys jobs*?" is evaluated with potential differences in the impact of product and process innovations in terms of economic performance.

The last aim of this thesis is to analyze the effect of product and process innovations on employment in Turkish manufacturing industries over the periods 1995-1997 and 1998-2000. We hypothesize that these two types of innovations have different impacts on employment and test this hypothesis by estimating two different econometric models. The first one is a treatment effect model controlling for the endogeneity of product and process innovations. The first stage of this

modeling explores the determinants of introducing product and process innovations by estimating a bivariate probit model by using the same explanatory variables utilized in the second analysis of this thesis. In the second stage, we estimate employment growth rate by treating the introduction of product and process innovations endogenous and by using firm specific variables like size, age and average wage rate, industry specific variables like concentration ratio and sectoral growth rate of output. In addition we incorporate measures of technological capability of firms like technology transferring and share of skilled employees and measures of characteristics of product and process innovator firms like size and age.

The second econometric analysis regarding the impact of innovations on employment is achieved by a selection model that controls for survival status of the firm. We estimate employment growth rate for firms that still exists in the industry in 2000 by Heckman selection model. The first stage of Heckman selection model explores the probability of firm survival by using firm size and age, labor turnover rate, labor productivity, capital intensity, debt ratio and concentration ratio as explanatory variables. In the second stage, we estimate employment growth rate under the condition that firm still exists in 2000 by using the same explanatory variables utilized in the previous employment growth rate modeling.

This thesis assesses how technology policy, R&D and innovativeness interact to yield higher economic performance linking the above mentioned three issues. Each of three issues is elaborated separately in the following three chapters. Moreover, each chapter provides a brief discussion on the theoretical framework and the empirical evidence, presents an overview for Turkish manufacturing industries on the explored subject, demonstrates the empirical models utilized to test the hypotheses and summarizes main findings. Finally, the last chapter dwells on the overall findings of this thesis and discusses possible policy implications.

CHAPTER II

R&D SUPPORT AND THE DEMAND FOR RESEARCHERS

2. 1. INTRODUCTION

The literature on technology policy has shown that the social rate of return to R&D is higher than the private rate of return, and emphasized the importance of R&D support programs to affect the rate and direction of technological change. There are a large number of empirical studies that assess the effects of R&D support programs on technological activities. A robust finding of these studies is the stylized fact that R&D support-receiving firms increase their expenditures on R&D activities, i.e., these programs are indeed successful in increasing R&D expenditures.

Some researchers claim that this increase in R&D expenditures in R&D support-receiving firms is mainly due to the increase in payments for researchers. Therefore, it is suggested that R&D support programs may simply subsidize the income of researchers without any significant real impact on R&D activities, and, hence, innovativeness.

This chapter focuses on the effects of public R&D support programs as an instrument of technology policy on the demand for researchers in Turkish manufacturing firms. We hypothesize that receiving R&D support encourages firms to demand more researchers to intensify their R&D activities. In order to test this hypothesis we estimate a two stage treatment effect model that solves the problem of selection bias. We first explore the probability of receiving R&D support by using firm size, profitability, previous R&D intensity, previous support receiving status and share of skilled employee as explanatory variables. We then estimate different labor demand specifications for researchers including support receiving status as an endogenous variable by using a firm level panel data

on manufacturing firms that performed R&D activities in the period 1993-2001. Labor demand equations include several measures of firm and technology specific indicators, such as firm size, previous support receiving status, sectoral R&D intensity, real output, input prices, the average wage rate and technology transfer.

This chapter is organized as follows. The next section provides a brief discussion on the theoretical framework and demonstrates the empirical evidence so far highlighting the divergence points of this study. The third section presents an overview of technology policy and R&D support programs in Turkey and analyzes the characteristics of R&D conducting and support-receiving firms in Turkish manufacturing industries separately. The fourth section demonstrates our empirical models in order to analyze the effects of R&D support receiving on the demand for researchers and summarizes main empirical results from these estimations. The last section briefly summarizes the findings of this chapter.

2.2. R&D SUPPORT AS AN INSTRUMENT FOR TECHNOLOGY POLICY: THEORETICAL FRAMEWORK

An analysis of technology policy instruments should first of all outline the approaches to technology policy in order to clarify the rationale for government involvement in knowledge generation. According to Metcalfe (1995), if we go back into the literature to find out the starting point to formalize the economic incentive to knowledge generation, we find that the first step was taken by Arrow and Nelson in 1950s. They clarified the economic peculiarities relating to production and diffusion of knowledge like indivisibilities, uncertainty, lack of appropriability, externalities and public good properties that interact and develop in different ways to produce the market failure and the social inadequacy of private incentive mechanism which are principle themes of traditional approach to technology policy (Metcalfe, 1994:931). They argued that the primary output of R&D investment is the knowledge and this knowledge is itself non-rival meaning that the use of knowledge by one firm does not prevent any other one to be able to use it and marginal cost of adding one more user of this knowledge is zero. This non-rival feature of knowledge makes the returns to the investment in R&D to be

incompletely appropriated by the firm undertaking the investment therefore bringing decreasing incentives to undertake R&D investments[1] (Hall, 2002:35).

The empirical support for market failure in relation to knowledge production- in terms of imperfect appropriation of returns and uncertainty- states that the social rates of return from R&D is higher than the private rates of return[2]. This line of reasoning provides a general rationale for technology policy instruments and outlines the policy recommendation that such socially beneficial knowledge generation should be publicly provided or subsidized via building necessary infrastructure and institutions. The policy tool suggestions of this classical market failure rationalization for public involvement can be summarized as creating favorable conditions to facilitate functioning of markets through competition policy and regulatory reforms, as enabling new markets for science and technology products through patent regulation, as managing public knowledge production and bringing correction essentials for these market failures through public provision and/or subsidizing private production of knowledge (Norgren and Hauknes, 1999:5).

Although market failure provides a general rationale for policy intervention in knowledge production and innovation processes, also outlining the traditional approach to technology policy, the government itself has been perceived as an important player in markets and hence bringing the government failure in technology policy agenda. Limitations of market failure analysis in technological progress have been analyzed in the 1980s and 1990s. This new modeling to technology policy, namely evolutionary approach disagrees with traditional approach that models technology policy on analytical grounds of a unique, competitive, welfare-maximizing equilibrium (Taymaz, 1993:556). According to

[1] Hall (2002) gives a further discussion about theoretical background for R&D investment funding. Although there may be underinvestment in R&D due to market failures, there is still an additional funding gap due to financial market reasons like venture capital eligibility for small firms and equity market formation differences between countries (Hall, 2002:48).

[2] Hall (1996) gives a detailed survey on the potential gap between the private and social returns to innovative activity. She argues about the problems in measuring the real returns to R&D and develops her argument giving an example that when the primary output of R&D is new products, the allocation of the measured returns to R&D between private returns and excess social returns depends on the price indices that are used (Hall, 1996:159). Counter to the finding of this study, Audretsch *et al.* (2002) evaluates net social benefits of SBIR program applied in US and finds that the net social benefits associated with this program is substantial.

evolutionary modeling of technology policy, technological progress is itself too complex and dynamic to be explained without involving heterogeneity, adaptation, variety and selection[3]. While market failure defines the equilibrium approach to technology policy making, evolutionary approach is concerned with technological change being endogenous and knowledge creation process both generating and also being influenced by uncertainty and imperfect information that shifts the attention of evolutionary policy maker from efficiency towards creativity, from equilibrium towards change and from optimization towards adaptation to market incentive and technological opportunity.

The distinction between equilibrium (traditional) and evolutionary approach to technology policy making defines the scope for the distinction between optimizing and adaptive approaches to policy making. Moreover, technology policy assumed to influence the rate and direction of innovative activity by two routes creating the crucial division between technology policy instruments which take the innovation possibilities of firms as given and those which seek to enhance these possibilities (Metcalfe, 1995:426). The policy instruments which take the innovation possibilities of firms as given try to reduce the cost of research to firm. R&D subsidies and tax incentives for R&D are typical R&D support instruments to change the pay-off to innovation. Instruments which are intended to shift the innovation possibilities of firms in a productivity enhancing way include collaborative R&D programs and policies to link the internal efforts of firms with public R&D carried out in the science base and research partnerships.

The choice of policy instrument for government in order to stimulate private R&D through public funding is classified broadly by Folster (1991) which is usually referred in the empirical literature. R&D support instruments are divided into two categories: *general* and *selective*, while selective R&D supports are further subdivided into self-financing and non-self-financing depending on whether the funding process includes an amount financed by R&D supported establishment's own funds (Taymaz, 2001:20). *General* R&D supports are fiscal incentives like tax deduction for R&D purposes and tax deduction for a rise in

[3] In the literature, the economics of technology policy is explored from neoclassical and evolutionary perspectives. Metcalfe (1994), (1995) and (2001), Lipsey and Carlow (1998) and Taymaz (1993) give further details for the comparison between two perspectives and their implications for technology policy.

R&D expenses. *Selective* R&D supports can be like fee-based loan guarantees, royalty grants and stock option grants that are grouped as self-financing on the one hand, and project grants, project loans at subsidized interest rates, loan guarantees and conditional loans that are repaid only if R&D is successful that are grouped as non-self financing on the other[4].

The aim of fiscal incentives to R&D is to make investment in R&D less costly to the firm and increase post-tax profitability by offering tax relief on R&D expenditures. The first one, tax allowances, is extra amounts over current business expenses deducted from gross income to arrive at taxable income whereas, the second, tax credits, are amounts deducted from tax liability (OECD, 2002:12). They allow markets to determine the allocation of R&D investments across sectors, firms and projects rather than governments by involving less interference in the market. Unlike funding of private R&D through selective supports, tax-based systems are easier to administer and horizontal in the sense that they are available to all firms according to precise criteria. The fiscal incentives to R&D are also less discretionary so that they do not allow governments to direct private R&D into special areas. However, fiscal incentives may create weaker spillover benefits to other firms and industries in comparison to selectively funded private R&D. The primary objection for fiscal incentives to R&D is that they are simply ineffective in raising private R&D expenditure due to low response elasticity and heterogeneity emerging from differences in taxable profits (Hall and Van Reenen, 2000:449)[5].

The funding of private research through selective R&D supports raise the private marginal rate of return on investment in such activities (David *et al.*, 2000:502). These R&D supports are rather vertical in the sense that they are selective and targeted to projects which are selected by governments to support industry. They have the advantage of allowing governments to keep control over

[4] We will call selective R&D supports as "R&D supports" and general R&D supports as "fiscal incentives to R&D" from this point onward. When we talk about publicly financed R&D, we take into consideration both general (which we call "fiscal incentives") and selective R&D supports.

[5] Hall and Van Reenen (2000) survey the econometric evidence on the effectiveness of fiscal incentives to R&D. They describe the effects of tax systems in OECD countries on the user cost of R&D, the methodologies used to evaluate the effect of the tax system on R&D behavior and give results from different studies using R&D investment equation in order to find the effect of fiscal R&D incentives on R&D investments. They conclude that the response to an R&D tax credit tends to be fairly small at first but increases over time stimulating private R&D spending (Hall and Van Reenen, 2000:466).

the nature of R&D conducted and target these supports toward projects that are perceived to offer high marginal social rates of return to investments in R&D (David *et al.*, 2000:502). However, the selective funding of public R&D brings the criticism of selection bias and this type of funding can also displace private R&D investments and distort market competition. Such R&D supports can create lock-in effect which will be difficult to phase out.

The policy instruments which take the innovation possibilities of firms as given and try to reduce the cost of research to firms like R&D supports need a further elaboration on theoretical grounds as we will analyze the economics of R&D supports in the following sections. Given the innovative possibility frontier, the firm is theoretically outlined as optimizing innovator (Metcalfe, 1995:428). If we consider a firm developing a new product which has a known demand curve with elasticity ε and if the amount X is spent in creating this innovation, the subsequent cost of production will be $C(X)$, which is the innovative possibility frontier, assuming that all innovation inputs are in perfectly elastic supply.

If we take the case of a profit maximizing monopolist, and assume that the marginal cost of a unit research effort is constant and equal to the wage paid to R&D employees (that can be taken as the only R&D expenditure due to being the largest component of it), then innovative effort is exactly proportional to R&D expenditure (Metcalfe, 1995:433). The R&D support policy that will be described here is to pay a subsidy to the firm at the percentage rate q on the R&D expenditure that it finances against its own profits. If X is the amount of self-funded R&D expenditure and if we choose the wage rate equal to unity for simplicity, the total expenditure becomes $X' = X(1+q)$.The firm chooses the profit-maximizing level of X' to satisfy:

$$-K(T) * Q_m \frac{\partial C}{\partial X'} = \frac{1}{1+q} \tag{2.1}$$

where $\frac{\partial C}{\partial X'}$ is the marginal productivity of R&D, Q_m is the profit maximizing scale of output and $K(T)$ is the present value factor which is the capital value of a stream of income discounted at rate r.

The above outlined R&D support mechanism actually has two different effects. The first effect (called *direct effect*) follows from holding the output of firm constant at the pre-subsidy level and the reduction in the marginal cost of research in the proportion of q due to subsidy that persuades the firm to increase its total research effort. This greater research effort leads to development of a superior process technology creating the *indirect effect* of R&D subsidy. As the superior technology is associated with lower unit production costs, it is also associated with a greater equilibrium output for the firm shifting the marginal profitability of research to the right[6] (Metcalfe, 1995:434).

In line with the theory, the empirical literature also classifies the effects of R&D supports into *direct* and *indirect* effects. However, David and Hall (2000) argued that the above mentioned direct and indirect effects are static and related to short-run. The static first–order effect, namely direct effect, is simply the short-run impact on prices of research inputs whereas, the second-order effect, namely indirect effect, includes the expected effects upon private sector rates of return where there is potential for crowding out (David and Hall, 2000:1171). They also pointed to another effect called *dynamic effect* concerning the consequences of the lagged responses of input supply and knowledge spillovers from previous results of R&D performed. However, in the empirical literature the effects of R&D supports are diversified into *direct* and *indirect* effects and these two effects are analyzed including the so called *dynamic* effect by controlling for previous R&D support experiences and by including lagged R&D investments.

The empirical literature evaluates the *direct* impact of R&D supports by modeling this effect on output growth, hence on productivity and R&D intensity. The finding that emerges from the impact on productivity growth is that privately-financed R&D contributes to productivity growth, whereas publicly-financed R&D supports have little or no direct effect. One of the empirical studies belonging to

[6] The simple mechanism explained above about the direct and indirect effects of R&D supports brings two central issues in policy towards research supports. The first one is the question of additionality which specifies that the total research effort that is increased by the subsidy may not follow that self financed component also increases (Metcalfe, 1995:434). The increase in self financed component needs further information about the elasticity of the firms' marginal profitability schedule to be given. The second issue relates the elasticity of supply of innovative inputs in judgment of the effects of R&D supports. Given the supply elasticity of R&D inputs different from perfect elasticity, the effects of any subsidy to research may not result in more research effort but in higher equilibrium wages for R&D employees.

this category is Capron and Van Pottelsberghe (1997) at macro level. They estimated total factor productivity growth rate for a panel of 22 industries for seven countries (including USA, Japan, Canada, France, Germany, Italy and UK) for the period 1980-1990 and found that private R&D has an impact on productivity growth but this impact is not higher than the impact of total R&D that is not disaggregated as privately and publicly financed R&D. In order to find the contribution of R&D supports in promoting the growth of output at industry level, Mamuneas and Nadiri (1996) analyzed the effects of publicly funded R&D on US manufacturing industries for 1956-1988 period using a cost function framework. They found that an increase in publicly financed R&D increases the efficiency and possibly stimulating output growth in terms of unit cost savings of the industries in the manufacturing sector (Mamuneas and Nadiri, 1996:78).

The second category of literature argues that the role of R&D supports is rather *indirect*, via the stimulation of private R&D investment[7]. The empirical literature of this second category, estimates private R&D investment model and provides mostly stimulating effect of R&D supports on private R&D expenditure especially at the macro level. Levy and Terleckyj (1983) examined the effects of public R&D investment on private R&D spending for US industry sector for the period 1949-1981 and found that public R&D investment stimulates private R&D expenditure. Another study, Guellec and Van Pottelsberghe (1997) analyzed the stimulating effect of R&D supports and fiscal incentives to R&D by estimating a R&D investment model that considers privately-financed R&D as a function of output, R&D supports, tax incentives and country-specific fixed effects for a set of 17 OECD countries. They found that both fiscal incentives and R&D supports stimulate private R&D investments in the shot-run and in the longer run R&D supports are more effective than fiscal incentives (Guellec and Van Pottelsberghe, 1997: 113).

[7] This category of existing literature focuses on whether public R&D expenditure is complementary and thus additional to private R&D expenditure or it substitutes for and tends to crowd out private R&D. David *et al.* (2000) survey the literature concerning the relationship between private and public R&D expenditure giving first the determinants of private R&D investment by firm-level investment behavior. David and Hall (2000), in another study, undertake a modeling exercise to outline possible different channels of influence by analyzing a framework to include labor supply effects of R&D employees.

The studies analyzing the impact of public R&D funding on private R&D expenditures at the firm-level are Meeusen and Janssens (2001) for Flemish Region of Belgium, Czarnitzki and Fier (2001) for German service sector and Koga (2005) for Japan high technology start-up firms. These country specific studies control for firm fixed effects, time effects, firm age effects, financial availability and past R&D intensity and previous R&D support experience. They found that firms that received public funding achieve a higher private R&D expenditure than firms that did not, leading to a complementary relationship between public and private R&D expenditure.

The empirical studies evaluating the effects of R&D support at firm level diverges from the macro level because using firm level data has changed the structure of modeling by making possible to introduce the determination of R&D support allocation process itself. Klette *et al.* (2000) review some micro econometric studies evaluating effects of public R&D funding on private R&D and focus on *selection bias*, *endogeneity* and *spillover issues* causing various different outcomes arising from the fact that participation in an R&D support program is not random. The potential selection bias comes from R&D support granting institutions that decide the recipient of R&D support whether depending on the applying firm and/or the relevant R&D project and this makes R&D support an endogenous variable in the analysis (Busom, 2000:114). Furthermore, granting institution might support only those firms and R&D projects that are expected to generate economic spillovers. This issue necessitates to be modeled as a counterfactual situation.

The first distinctive modeling regarding the impact of R&D supports at firm level by taking into account the selection process was applied by Irwin and Klenow (1995) for US Sematech program for the period 1970-1993. They compared the research effort of Sematech member firms with non-member firms and estimated R&D intensity of those firms by controlling for firm fixed effects, time effects, firm age effects and past R&D intensity. They found that member firms' R&D intensity decreased and pointed out the importance of the validity of the control group.

The studies in the empirical literature paying attention to potential selection bias diverge from each other by their econometric modeling of this bias. Lach (2000) analyzed the impact of public R&D funding on private R&D expenditures

using firm level data on Israeli manufacturing firms for the period 1990-1995. He defined R&D support effect as the average percentage change in privately financed R&D expenditures between what was actually observed among firms that received R&D support and what these firms would have spent if they did not receive R&D support (Lach, 2000:32). His model was a treatment effect model using a difference in differences (DID) estimator[8], controlling for the source of correlation that may rise due to the fact that the characteristics that make a firm R&D support recipient are likely to be correlated with the determinants of firms' own R&D expenditure. He found a positive but insignificant public R&D funding effect on privately financed R&D expenditure.

Another empirical tool that takes care of selection bias formulation was utilized by Almus and Czarnitzki (2001) who used firm level data for Eastern Germany. They applied non-parametric matching approach[9] where they were first able to find a counterpart for every firm that received R&D support by matching with a non supported one. Later, they identified the effect of R&D support receiving since they were able to approximate a situation where there were no differences between R&D support receiving and non receiving firms with respect to characteristics that may influence the probability to receive R&D support (Almus and Czarnitzki, 2001:4). After estimating the probability of receiving R&D support by controlling for size, age, market share and export intensity of firms, they tried to assess whether firms that received R&D support have on average a higher R&D intensity compared to firms that did not receive support. They found that

[8] In simple difference estimator, the mean of R&D expenditures of the non supported firms is taken as an estimate of the counterfactual and the estimator could be the simple difference in mean R&D expenditures by support status (Lach, 2000:17). However, in case of difference in differences estimator (DID), which is just error correction component of simple difference estimator, the author controls for all unobserved characteristics that are potentially correlated with R&D support status and decompose them into a firm-specific and time-specific effect. By this way, the author allows both firm and time specific effects to affect both the level of private R&D expenditure and the support status of firm. For further discussion about this method see Lach (2000).

[9] The authors applied a non-parametric matching approach that was developed by Roy (1951). This approach rests on the condition that participation (receipt of R&D support) and the potential outcome (R&D intensity) are independent for individuals with the same set of exogenous characteristics (Almus and Czarnitzki, 2001:10). This condition means that there are no systematic differences between firms that received R&D support and firms that did not, which is not a proper condition for defining all selection biases. For further discussion about this method see Almus and Czarnitzki (2001).

firms that received R&D support achieve a higher R&D intensity than firms belonging to the selected control group (Almus and Czarnitzki, 2001:25).

Busom (2000) explored the problem of selection bias by applying a two stage econometric treatment model including a participation equation and R&D effort equation. The analytical tool used in this study was parametric selection model[10]. In the first stage, she estimated a probit model on the participation probability in R&D support programs using Heckman sample selection models. In the second stage, the R&D effort equation in terms of R&D expenditures is regressed on several covariates including a selection term which accounts for different probabilities of firms to be a recipient of R&D support. She found that being small, domestic ownership and previous experience in R&D were positively associated with participation status and overall public R&D funding induces more private R&D effort for Spanish manufacturing firms (Busom, 2000:128).

In a later study, Blanes and Busom (2004) used a sample of Spanish manufacturing firms for the period 1990-1996 and estimated a similar model to solve for selection bias. The difference between two studies lies in the method that they used in the first stage selection process. In this study, they defined three participation statuses (not doing R&D, doing R&D but not participating in R&D support programs and doing R&D and participating in R&D support programs) and used multi-nominal logit models to estimate participation probability in R&D support programs. They found similar results with Busom (2000) and concluded that previous experience in R&D is always positively associated with participation status but the effects of firm size, cash flow, ownership and human capital intensity on participation status differ with different goals of the support program (Blanes and Busom, 2004:1474).

In a recent study, Hussinger (2003) made use of parametric two-step selection model and in addition semi-parametric selection models to evaluate the effect of R&D supports on the R&D expenditure of firms in German

[10] Selection models provide an appropriate method if we have two observed subgroups (like R&D support receivers and non-receivers) and when these two subgroups are not randomly emerged but are results of a selection process. The details of selection modeling will be outlined later in the empirical modeling part of this study.

manufacturing sector[11]. In the first step, the author similar to Busom (2000), estimated a probit model on the probability to receive R&D support and found that firm size, market share, market concentration and past innovative activities affect the probability of receiving R&D support (Hussinger, 2003:15). In the second step, she estimated R&D expenditure equation taking into account the selection process and found that the strongest impact on R&D expenditure stems from the firm size.

Although the above mentioned literature provided the insights into R&D supports that have stimulating R&D investment effects and productivity growth effects with or without taking into account the selection process itself, little research has tended to focus on the relationship between employment and public R&D funding. To best of our knowledge, Goolsbee (1998) is the first study to analyze the direct labor market effects of public R&D funding. He found that increases in expenditures for public R&D have a significant effect in raising average scientists and engineers wage in US. His line of reasoning is that the majority of R&D spending is actually payments to R&D employees and the supply of R&D employees is quite inelastic. He explained log real income of R&D employees by total R&D spending as a part of GDP and concluded that public R&D spending brings gains to R&D employees (Goolsbee, 1998: 299). However, a different framework is applied by Lerner (1999) where he analyzed the effects of Small Business Innovation Research (SBIR) on employment growth rather than on R&D employees' wage. He explored changes in employment by controlling for different R&D support receiving firm characteristics, sales and the volume of previous venture capital of firms. He found that presence of R&D supports alone had little relationship with employment growth (Lerner, 1999:308).

A recent study, Reinthaler and Wolff (2004), investigated the effectiveness of R&D supports to private R&D employment on macroeconomic level using a panel data set of 15 OECD countries from 1981 to 2002. Their departure from other studies is that they used the subsidy rate instead of aggregate R&D support payments. They estimated the number of R&D employees by using openness

[11] The difference between parametric and semi-parametric selection models rests on the consistency issues. Parametric estimators are more efficient than semi-parametric estimators, yielding a more exact estimator provided that the model specification is correct. However, if the common distribution of the error terms is not correctly specified, these estimators become inconsistent (Hussinger, 2003:8). The details of this difference between these two methods will be described later in the econometric modeling part of this study.

measured by the ratio of exports plus imports over GDP, real GDP measured by purchasing power parity and subsidization rate measured by average subsidization of private sector by the government as explanatory variables. They also looked for dynamic effects of R&D supports on the number of R&D employees by including lagged values of R&D employees. They found that subsidy rate has a positive and significant effect on R&D employment and this effect is even larger in the long-run (Reinthaler and Wolff, 2004:17).

The empirical studies that focus solely on the employment effect of R&D supports without taking into account the selection process and endogeneity of these R&D supports will be misleading. While any analysis that is based on regressing some measures of employment on R&D support variables can establish a correlation between R&D supports and employment, it can not determine whether receiving R&D supports cause firms to employ more employees or whether firms that employ more employees have an increasing probability to receive R&D supports.

Wallsten (2000) is apparently the first study going one step further that takes the selection process into account in analyzing employment effects of R&D supports. He estimated a multi equation model that determines whether R&D supports cause firms to do more innovative activity or whether firms that do more innovative activity receive more R&D supports separately. He chose sales and employment of firms as representatives of innovative activity. He assembled a firm level data on US SBIR program constituting of two groups of firms, one that received R&D supports and the other applied for R&D support but has been rejected. He estimated a simultaneous equation system which controls for the selection of which firms have received R&D support and instrumented the budget of SBIR program for controlling the endogeneity of awards. Controlling for age, previous employment, dummy for ownership, previous R&D spending and number of patents for period 1990-1995, he found that firms with more employees receive R&D supports but supports do not lead to increased employment (Wallsten, 2000:98).

A recent study by Romer (2000) has signaled a necessary switch in perception of technology policy and in its targets directed at by using instruments like R&D supports. He argued that increasing the spending on R&D as an

instrument of technology policy is a necessary but not a sufficient condition to have economic development to speed up (Romer, 2000:14). In addition to that, technology policy should increase the quantity of inputs that go into the process of R&D. With this line of reasoning, he brought a new discussion into the effects of R&D supports in connection to demand for and supply of R&D employees.

Romer, in order to simplify his discussion, assumed that R&D employees are the only inputs in R&D that is a similar modeling elucidated before by Metcalfe (1995). The simple downward-sloping demand curve for R&D employees represents the private return captured by a single firm that hires some additional R&D employees and undertakes more R&D. If this single firm receives R&D support, it is obvious that firm will be encouraged to devote more inputs to R&D by increasing its demand for R&D employees. Furthermore, any increase in R&D spending may not necessarily translate into a corresponding increase in the number of R&D employees if the total number of R&D employees is fixed (Romer, 2000:17). If the supply curve of R&D employees is fixed (having zero elasticity), then the increase in the demand induced by R&D support will translate into a proportional increase in wages for R&D employees with no increase in the inputs devoted to R&D process[12].

This study focuses on *the effects of public R&D support programs on the demand for R&D researchers*. It departs from other studies because we focus on the effects of R&D supports on the number of researchers employed by utilizing both static and dynamic labor demand modeling framework. Another point of departure from the literature is that, we explore *the problem of selection bias* and apply a two stage econometric treatment model to define determinants of the probability of receiving R&D support.

[12] A priori, it is not clear whether one should expect R&D labor to be elastic or inelastic in supply.

2.3. CHARACTERISTICS OF R&D SUPPORT RECEIVING FIRMS: DESCRIPTIVE ANALYSIS

2.3.1. OVERVIEW OF TECHNOLOGY POLICY AND R&D SUPPORT PROGRAMS IN TURKEY

Search for a formalization of national policy in science and technology have started with planned economy in Turkey. The first institution Scientific and Technical Research Council of Turkey (*TÜBİTAK*), marking a turning point, is established in 1963 with **The First Five Year Development Plan** (1963-1967) for the purpose of coordinating, organizing and promoting research in the basic and applied sciences (TÜBİTAK, 1999:1). Over the years, TÜBİTAK has expanded its chief function from supporting basic research towards industrial technological activities. In the later plan documents, technological development and technology transfer have been taken into consideration but in 1960s and 1970s, the basic policy in science and technology was the promotion of basic and applied research in natural sciences. In **The Fourth Five Year Development Plan** (1979-1983), the concept of '*technology policy*' has been mentioned for the first time. This plan also emphasizes the need for integrating technology policies with industry, employment and investment policies.

At the beginning of 1980s, a detailed science and technology policy document, **Turkish Science Policy: 1983-2003** was prepared recognizing the role of technology for development and suggested priority areas of technology. This approach has created a new institution: The Supreme Council for Science and Technology (*BYTK*) in order to design science and technology policies, as the highest science and technology policymaking body chaired by the Prime Minister or his deputy. In the mid-1990s, the Supreme Council started to play an active role in formulating the national science and technology policy as the central component of the national innovation system. In 1993, BYTK approved a second policy document entitled "**Turkish Science and Technology Policy: 1993-2003**". This document emphasized the determinant role of science and technology in respect of surviving the vitality of national economy, sustaining economic growth, upgrading the living standards and international competitive advantage (TÜBİTAK, 1999:6). Taking into account Turkey's capabilities and technological trends, informatics,

advance materials, biotechnology and space technology have been accepted as priority areas of activity. This was a turning point in the science and technology policy era in Turkey, as there was a paradigm shift from building a modern R&D infrastructure to innovation oriented national policies (TÜBİTAK, 2004:5)[13].

The recognition of the key to enhance competitive advantage in industrial enterprises through productivity improvements and hence technological innovation, started to shape Turkey's science and technology strategy (Elçi, 2003:23). This strategy calls for adoption of systematic innovation finance programs. The first institution to fulfill this requirement, Technology Development Foundation of Turkey (*TTGV*), was established in 1991 and has provided loans for industrial R&D projects since 1992. TÜBİTAK also initiated an R&D grant program in 1995 for industrial R&D projects and established a special division *TİDEB* in charge of the program. Both programs co-finance the expenditures of R&D projects carried out by industrial companies.

TTGV has become one of the main agencies to provide funding for R&D in Turkey. TTGV acts as the implementing agency for the funds provided from Under-Secretariat of Treasury through the World Bank loan for supporting R&D activities in the form of R&D loans (Elçi, 2003:27). TTGV used to provide conditional loans subject to commercialization, but this practice was replaced by interest free *R&D loans*. TTGV supports projects for a maximum of two years, and the support amount cannot exceed 50 percent of the project budget. The amount of support can not exceed USD 2 millions if it is granted by Under Secretariat of Treasury and this amount is USD 1 million for the supports from Under Secretariat of Foreign Trade (TTGV, 2001:5). R&D loans given by TTGV are extended in terms of USD without any interest, but a fee (2-3 % of the project budget) is to be paid for administrative expenses. The loans have to be repaid over three to five years after a one-year grace period.

The first project initiated by TTGV, *The Technology Development Project (TDP)*, was financed by the Under-Secretariat of Treasury through the resources of the World Bank. TDP was implemented between years 1991-98 with a budget amounted to €108 million which was utilized for facilitating R&D activities of

[13] For further discussion on evolution of technology policy perspectives and institutions shaping national innovation system of Turkey, see Taymaz (2001), Elçi (2003) and TÜSİAD (2003).

business sector (Elçi, 2003:13). *The Industrial Technology Project (ITP)* which is a follow-up to the World Bank's Technology Development Project (TDP), was implemented between years 1999-2003 with a total amount of €162 million aiming to enhance industrial R&D.

The technology development projects that are supported by TTGV should realize product and process innovations whose scope is defined by the institution[14]. TTGV gives support to technology development projects in two phases, first involving the realization of process and product innovation and the second involving the marketing and competitiveness. The expenditure items that are divided between TTGV and supported firm are personnel expenditures, expenditures on tools and machinery needed for developing product and process innovations, consultancy expenditures paid to technology research institutes and universities, expenditures on telecommunications, patent applications and personnel training, expenditures on transportation and insurance amount for the machinery and equipment (TTGV, 2001:14).

TİDEB started to provide *R&D grants* to industrial R&D projects in 1995. It also assists the government on the implementation of R&D tax postponement scheme and R&D investment schemes (Elçi, 2003: 27). In the context of the R&D support program, TİDEB serves as the referee institution, where the Under Secretariat of Foreign Trade provides funding, which accrues to firms at a rate of up to 60 % of R&D expenditures in terms of TL.

If a technology development project is found proper to support by TTGV, TİDEB also give grants for this project without analyzing the project. TİDEB grants are given to projects for a maximum of three years, and the support amount cannot exceed 50 percent and this amount can be at a maximum of 60 percent of the project budget with additional supports. This additional amount can be granted if the supported R&D activity ends up with patent or if the supported project is in the area of information, flexible production, environment and space technology. The R&D expenditure items covered by TİDEB are personnel expenditures, expenditures on tools and machinery, consultancy expenditures paid to technology

[14] The support application document TTGV (2004), gives definition of process and product innovations and other application procedures in detail.

research institutes and universities and expenditures on patent applications and personnel training.

Concisely, we can give a brief evaluation of R&D support programs initiated by TTGV and TİDEB[15]. For the period 1995-2003, 937 firms with a total number of 2193 projects have applied to TİDEB for receiving R&D grants and the number of projects that have been accepted and supported is 1430 (TÜSİAD, 2003:96). For this period, the number of projects that have been completed is 852 and the average amount of support paid to these projects is 14 million USD, yearly. For the period 1992-2002, the number of projects that have applied to TTGV for receiving R&D loans is 923 and the number of projects that have been supported is 318. The average amount of support paid to these projects is 10 million USD, yearly (TÜSİAD, 2003:96).

2.3.2. OVERVIEW OF R&D ACTIVITIES AND R&D SUPPORT SCHEME IN TURKEY

After giving a rough idea about technology policy perception of Turkey, we will analyze the structure of R&D activities and profile of R&D support programs in Turkey. The R&D activities in Turkey are conducted by firms that are operating in manufacturing industry, service and computer service sectors. The number of firms conducting R&D and the amount spent on R&D are continuously increasing in Turkey and the number of R&D conducting firms and their R&D spending has nearly doubled during the period 1993-2002 (Table 2.1). The firms that conduct R&D activities are dominated by manufacturing sector firms. The number of manufacturing firms conducting R&D constitutes 72 % of total number of R&D conducting firms and the amount of R&D expenditures made by these firms constitutes 86 % of total R&D spending in 2002. The only sharp decrease in R&D expenditures is in 1994 pointing the economic crisis year for Turkey. Moreover, the average R&D size, which is measured by R&D expenditures over the number of R&D conducting firms, is also affected from this crisis but still has an increasing pattern for the period 1993-2002.

[15] Taymaz (2001) gives a detailed evaluation about technology support programs in Turkey. He also reviews the profile of applicant firms and technology support services using a survey conducted by State Institute of Statistics (SIS).

Table 2.1. Total R&D Expenditures, Number of R&D Conducting Firms and Average R&D Size

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
R&D expenditures (million USD, PPP)										
All	410.3	275.2	301.0	463.6	628.6	648.2	966.1	976.9	1033.5	867.7
Manufacturing	328.6	253.7	276.2	427.4	495.6	542.0	822.2	840.8	921.6	745.3
Number of R&D conducting firms										
All	192	218	219	280	410	431	432	459	373	373
Manufacturing	175	194	200	232	313	331	325	338	302	269
Average R&D size per number of firms (thousand USD, PPP)										
All	2137	1262	1375	1656	1533	1504	2236	2128	2771	2326
Manufacturing	1877	1308	1381	1842	1584	1637	2530	2488	3052	2770

Source: State Institute of Statistics

Expenditures devoted to R&D include current costs and capital expenditures according to *OECD Frascati Manual* (2002). The current costs are composed of labor costs of R&D personnel and other current costs that include non-capital purchases of materials, supplies and equipment to support R&D performed like materials for laboratories. Capital expenditures are the annual gross expenditures on fixed assets used in R&D programs and composed of expenditures on land and buildings (labeled here as *building*) and instruments and equipment (labeled here as *machinery*) (OECD, 2002:111). In Turkey, the decomposition of R&D expenditures is the same as other countries where labor costs constituting the highest share in total R&D expenditures (Figure 2.1). The highest amount of R&D expenditure is devoted to R&D personnel until 1998 and the lowest amount is spent on fixed assets that include expenditures on building etc. After 1997, relatively more R&D expenditures were devoted to capital expenditures especially on instruments and equipment, labeled here as machinery and the amount spent on machinery and equipment becomes the highest value constituting nearly 50 % of total R&D expenditures in 2002. Moreover, we see the effects of financial crisis that happened in 1994 and 1998 on the amounts spent by a sharp decrease observed in the R&D expenditure values.

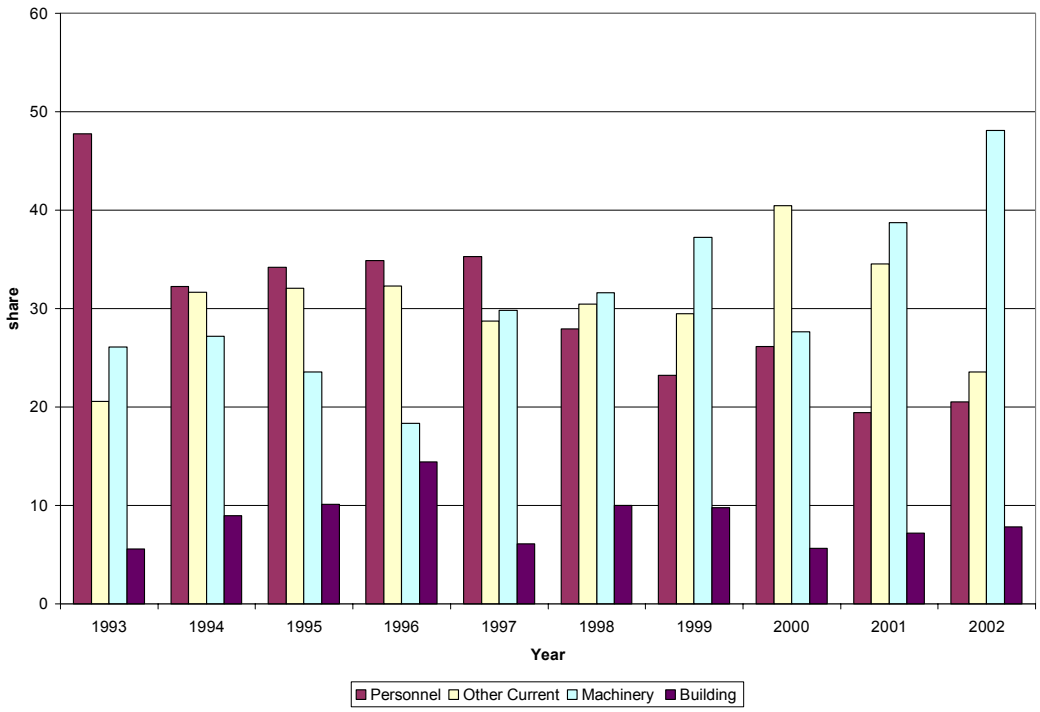

Figure 2.1. Share of R&D Expenditures by type, 1993-2002, (percentage)

Source: State Institute of Statistics

As we mentioned before, R&D conducting firms dominantly operate in manufacturing. From this point onward, the analysis about R&D activities will be based on R&D conducting firms operating in manufacturing industry. R&D activities in Turkey mainly financed by firms' own source and the share of this source of finance is 93 % in 2002 (Table 2.2). The share of public institutions as a source of R&D financing has been increasing throughout the period and reached 3 % of total R&D expenditure in 2002. For the crisis years 1994 and 1998 and post crisis periods, foreign sources seem to become a secondary source of R&D financing for manufacturing firms. Another point of interest is that there is nearly ignorable amount of partnership between R&D firms and universities in Turkey.

Table 2.2. Share of R&D Expenditure by Source of Finance, 1993-2002, (percentage)

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Own source	98.6	92.8	90.9	98.4	94.1	96.6	83.8	92.2	95.2	93.0
Public	0.1	1.7	1.8	1.0	2.5	1.6	1.5	4.7	3.5	3.1
Private	0.5	0.3	0.5	0.3	0.7	0.3	0.2	0.2	0.7	1.5
University	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Foundation	0.4	1.6	0.6	0.3	2.0	1.4	0.5	1.0	0.5	1.0
Foreign	0.4	3.5	6.1	0.0	0.7	0.1	14.0	1.8	0.1	1.5

Source: State Institute of Statistics

The data on firms choosing their own sources to finance R&D does not necessarily lead us to conclude that these firms do not face difficulties in financing R&D. Although these firms may have received R&D supports from TTGV and/or TİDEB, they still have to finance at least 50 % of the supported budget. So, by looking at the above table and concluding that the share of public institutions as a source of finance in R&D activities being relatively small is a misleading inference.

R&D supports granted by TTGV and TİDEB is summarized for the period 1992-2002 in Table 2.3. The data in this table is designed according to the implementation period of R&D project and covers all supported firms including firms in service and computer service sectors. The number of firms receiving R&D support has continuously increased with the initiation of these support programs and reached 91 and 338 in 2002 for TTGV and TİDEB, respectively. The number of firms receiving support from TİDEB was larger than that of TTGV. This can be explained by different R&D support schemes of TTGV and TİDEB. TTGV provides R&D support in the form of interest free R&D loans denominated in USD whereas TİDEB gives R&D supports in the form of R&D grants denominated in TL which makes it financially more attractive relative to TTGV R&D loans (Taymaz, 2001:165). The value of projects supported also increased similarly following the first initiation year support programs.

Table 2.3. R&D Supports of TTGV and TİDEB, 1992-2002

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Number of support receiving firms											
TTGV	6	18	23	27	55	72	67	58	75	81	91
TİDEB				60	157	216	259	240	246	278	338
Value of projects supported (thousand USD, PPP)											
TTGV	665	7649	12100	15347	27590	60795	54670	21634	40164	51652	48188
TİDEB				34585	86624	130814	170201	199005	205153	228202	199957
Value of supports (thousand USD, PPP)											
TTGV	318	3711	5665	7188	12697	29769	29295	11341	20040	25497	24050
TİDEB				6391	16241	28301	42086	52152	60473	92798	98861
Subsidy rate (%)											
TTGV	9.2	8.0	8.4	8.4	9.7	10.1	11.7	13.3	12.6	12.5	7.9
TİDEB				16.8	18.5	20.7	23.4	26.7	31.8	43.7	53.3
Subsidized R&D expenditure rate (%)											
TTGV		55.6	62.1	46.8	65.6	76.7	74.5	73.0	75.3	76.6	79.7
TİDEB				54.4	69.2	72.7	74.5	76.7	67.9	75.1	78.4

Source: State Institute of Statistics

The subsidy rate for TTGV is calculated as a share of R&D project budget. We assumed that the loan will be paid back in 2.5 years and calculated the fee component taking the interest rate on one year deposit in USD. After finding the subsidy part, we deducted project fee from subsidy part and divided it by project budget. The subsidy rate for TİDEB is calculated as value of TİDEB support on the project divided by the value of the project budget since there is no fee component for TİDEB. The average subsidy rates have been 10.2 % and 29.3 % for TTGV and TİDEB projects, respectively. We also calculated the subsidized R&D expenditure rate that is the value of R&D project expenditures divided by the value of total R&D expenditures for TTGV and TİDEB clients separately. The average rate has been 68 % and 71 % for TTGV and TİDEB projects, respectively. This rate has been higher for both TTGV and TİDEB because we did not consider for fee and interest rate components and we took into account only the supported project budgets.

Table 2.4. Share of TTGV Supported Projects by Technology Level, 1992-2002, (percentage)

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
HIGH	41	48	40	47	22	27	40	29	40	36	27
MEDIUM	12	13	22	36	31	43	29	53	41	52	63
LOW	47	39	38	17	46	30	31	18	19	12	10

Source: State Institute of Statistics

We further explore TTGV and TİDEB R&D support programs by classifying supported projects by technology level[16]. For TTGV, there is no clear cut evidence to decide which technology level has the highest share in the supported projects (Table 2.4). However, in 1993, the first initiation year of TTGV program, the share of projects supported in high technology industries was the highest (48 %). After 1995, the share of supported projects in medium technology industries started to increase and reached 53 % in 1999 coinciding with the initiation year of ITP, constituting 63 % of the total value in 2002. In line with this finding, the share of projects supported by TTGV in low tech industries has declined to 10 % of the total value for this year. The only clear inference about TTGV projects by technology level is that during the period, the share of projects supported in low technology industries has declined in contrast to the increase in medium technology industries.

When we classify TİDEB supported projects by technology level (Table 2.5), we can say that the share of projects supported by TİDEB in medium and high technology industries moved together and both constituted nearly 90 % of total value. Moreover, the share of projects supported in medium technology industries never fall below 40 % of the total value. The share of value of projects supported by TİDEB in low technology industries was low but after 1997, this share started to decrease sharply constituting 7 % of the total value in 2002. So, it will not be

[16] We classified the manufacturing industries into three categories according to their technological level. These categories are low tech, medium tech and high tech industries. The industries in low tech, medium tech and high tech were defined according to OECD classification and listed in Appendix.

misleading to conclude that the projects supported by TİDEB dominantly belong to high and medium technology industries.

Table 2.5. Share of TİDEB Supported Projects by Technology Level, 1995-2002, (percentage)

	1995	1996	1997	1998	1999	2000	2001	2002
HIGH	47	38	40	42	31	34	37	50
MEDIUM	43	45	40	47	62	60	57	42
LOW	10	17	20	11	7	6	6	7

Source: State Institute of Statistics

2.3.3. R&D CONDUCTING AND SUPPORT RECEIVING FIRMS IN TURKISH MANUFACTURING INDUSTRY

Up to this point, we tried to analyze the general characteristics of R&D conducting firms, R&D conducting firms in manufacturing industries and R&D support schemes for TTGV and TİDEB clients. In order to make comparisons between R&D support receiving firms and R&D conducting firms and to have a control group for firms that did not receive support, we matched three data sets for manufacturing industry firms. The first data set constitutes of a survey covering the period from 1992 to 2001 and containing data on all manufacturing firms employing more than 10 employees. The second data set constitutes of an R&D survey, covering the period from 1993 to 2002 and containing data on R&D expenditures, employment etc. and covers all manufacturing establishments known to perform R&D activities as defined by *OECD Frascati Manual* (2002). These two surveys are conducted by SIS annually and after matching, this study covers the period from 1993 to 2001. Finally, a data set for all TTGV and TİDEB support receiving clients was prepared. It covers the basic data on all projects (the project budget, the amount of support, the duration of project etc.) supported by these

institutions. Combining three data sets, we had all R&D conducting and support receiving manufacturing firms employing more than 10 employees.

When we look at support receiving firms that are also covered by R&D survey (Table 2.6), we see that some of the support receiving firms did not coincide with the firms that conduct R&D activity. The share of support receiving firms that are also covered by R&D survey was 3.5 % in 1993 and has increased and reached to 25 % of total firms covered in R&D survey for 2002. The number of support receiving R&D conducting firms constitutes nearly 16 % of total TTGV support receiving firms in 2002 whereas this rate is 20 % for TİDEB. The average subsidy rate for support receiving R&D conducting firms is 10 % and 29 % for TTGV and TİDEB projects, respectively.

Table 2.6. R&D Supports of TTGV and TİDEB for R&D Conducting Firms, 1993-2002

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Number of support receiving firms										
TTGV	6	7	13	25	22	25	18	35	22	15
TİDEB			30	67	77	94	81	95	73	67
Value of projects supported (thousand USD, PPP)										
TTGV	3094	3868	7935	17581	21173	17329	5265	21948	19112	9330
TİDEB			27668	65526	68342	109754	148381	173205	157582	90664
Value of supports (thousand USD, PPP)										
TTGV	1487	1759	3721	8006	9946	8466	2458	10852	9499	4665
TİDEB			5218	12412	13466	26407	37532	49520	60406	50921
Subsidy rate (%)										
TTGV	7.7	8.2	8.2	9.7	10.0	11.5	13.0	12.5	12.3	7.8
TİDEB			17.7	18.8	19.8	22.7	26.6	32.3	43.2	53.6

Source: State Institute of Statistics

After combining three data sets (manufacturing firms employing more than 10 employees, R&D conducting firms and support receiving firms), in order to explain differences between firms that conduct R&D activity and that do not conduct R&D activity, or firms that receive R&D support and that do not receive R&D support, we grouped the establishments into "*All*", "*R&D conducting*" and

"*Support receiving*". For example, if we want to compare firms that conduct R&D activity with firms that do not conduct R&D activity, we will use the values in "*R&D conducting*" and "*All*". Another possible comparison between R&D support receiving firms and firms that do not receive R&D support (note that support receiving firms are also matched with R&D conducting firms) will be between the values in "*Support receiving*" rows and "*R&D conducting*" rows.

As we try to find any effect of conducting R&D and/or receiving R&D support, we will look at the average R&D size of firms (Table 2.7). The average R&D size of R&D conducting firms is relatively larger than R&D size of non-conductor firms. As mentioned in the literature, one of the effects of R&D supports is to increase privately financed R&D spending. This effect can be seen in support receiving firms because the average size of support receiving firms is higher than both R&D conducting and not conducting firms. The last row of the table demonstrates the ratio of support receiving firms' R&D expenditures over R&D conducting firms' expenditures. As we see, this ratio is continuously increasing until 1999 and R&D expenditures devoted by support receiving firms reached 80 % of total R&D expenditures devoted by R&D conducting firms in 2001.

Table 2.7. Average R&D Size, 1993-2001, thousand USD, PPP

	1993	1994	1995	1996	1997	1998	1999	2000	2001
All	18	23	29	26	41	38	47	59	37
R&D conducting	2055	1570	1733	2322	1900	1851	2644	2927	3567
TTGV	15992	12207	8005	7339	6032	3267	3895	3876	12784
TİDEB			6372	5321	3645	5223	9089	8473	10456
Support receiving	15992	12207	5887	5321	3651	5109	8656	7995	9876
Supp/R&D (%)	27.6	31.7	69.4	74.0	58.5	81.4	85.1	80.5	80.1

Source: State Institute of Statistics

The average R&D size is an important tool in evaluating the differences between R&D conducting and support receiving firms. The decomposition of R&D

expenditures devoted by R&D conducting and support receiving firms by technology level is also informative about R&D activities conducted in Turkey (Table 2.8). The share of R&D expenditures allocated by R&D conducting firms moves closely for high and medium technology industries up to year 1996. Starting from 1997, R&D expenditures devoted to medium technology industries reach 50 % of total R&D conductors' expenditure and stay above this amount for the rest of the period. However, support receiving firms allocate their R&D expenditures mostly in high technology industries until 1998. For the last four years, R&D expenditures allocated to medium technology industries turn into the highest of all industries. We have to mention lastly that R&D conducting firms allocated on the overall 20 % of their R&D expenditures to low technology industries but this amount is rather small for support receiving firms.

Table 2.8. Share of R&D Expenditures by Technology Level, 1993-2001, (percentage)

	1993	1994	1995	1996	1997	1998	1999	2000	2001
R&D conducting									
HIGH	40	42	44	37	29	22	17	25	28
MEDIUM	43	39	39	37	50	63	73	63	55
LOW	17	19	17	26	21	14	10	12	17
Support receiving									
HIGH	68	67	55	44	42	24	18	27	29
MEDIUM	32	33	34	31	40	67	77	68	62
LOW	0	0	10	25	18	9	5	6	9

Source: State Institute of Statistics

After a brief discussion about the allocation of R&D expenditures in R&D conducting and support receiving firms separately, we will explore the pattern of firms (Table 2.9). The first point to highlight is that the number of R&D conducting firms increases for the whole period and this rise in number between 1993-2001 is 80 %. However, as Figure 2.2 depicts, the number of R&D conducting firms constitutes only 2 % of total manufacturing firms in 2001. The number of support receiving firms increased nearly 13 times when we reached at

the end of the period. Starting from 1995, the share of R&D support receiving firms in R&D conducting firms is 28 % on the average. The jump seen in the share of support receiving firms is due to the fact that 1995 is the initiation year of TİDEB support program which has relative financial attractiveness than TTGV support program and we observe a rise in the number of support receiving firms in that specific year.

Table 2.9. Number of Firms in the database, 1993-2001

	1993	1994	1995	1996	1997	1998	1999	2000	2001
All	10,565	10,125	10,190	10,584	11,371	12,321	11,262	11,112	11,305
R&D conducting	141	147	142	161	243	278	277	275	235
TTGV	5	6	12	18	19	21	16	27	19
TİDEB			26	52	73	79	68	76	64
Support receiving	5	6	29	52	74	82	72	81	68

Source: State Institute of Statistics

Next we will analyze the share of R&D conducting and support receiving firms separately according to their classification between industries with different technological orientation (Table 2.10). The share of firms conducting R&D in medium and low technology industries constitutes the highest amounts and they follow the same trend until the end of the period constituting nearly 80 % of R&D conducting firms together. For all of the years, the R&D conducting firms belonging to high technology industries have the lowest share in total and they constitute 19 % of R&D conducting firms in 2001. This can be explained by the difficulties high technology industry firms face due to uncertainty and size considerations. However, support receiving firms dominantly operate in medium technology industries starting from 1995. The share of support receiving firms operating in medium technology industries is 44 % in total support receiving firms in 2001.

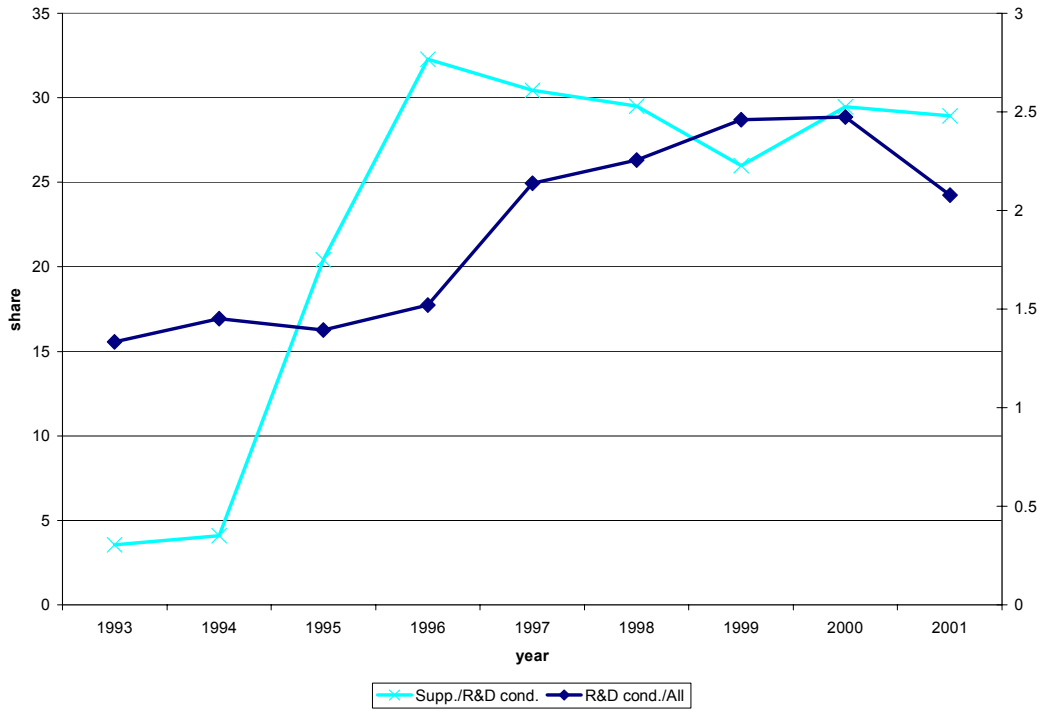

Figure 2.2. Share of R&D conducting and support receiving firms, 1993-2001, (percentage)

Source: State Institute of Statistics

Table 2.10. Distribution of R&D conducting and Support-receiving Firms by Technology Level, 1993-2001, (percentage)

	1993	1994	1995	1996	1997	1998	1999	2000	2001
R&D conducting									
HIGH	26	21	22	20	18	18	17	19	19
MEDIUM	37	40	37	40	40	42	43	43	34
LOW	37	39	42	39	42	40	40	39	47
Support receiving									
HIGH	60	67	34	25	23	22	24	25	28
MEDIUM	40	33	45	48	45	48	42	47	44
LOW	0	0	21	27	32	30	35	28	28

Source: State Institute of Statistics

The empirical works on the structure of Turkish R&D activities reveal that the most important aim of R&D activities is to solve operational and technical

problems faced in product and process innovations (Taymaz, 2001:170). So, we further elaborated whether technology transfer is a substitute of conducting R&D or not. The share of technology transferring firms in R&D conducting firms is larger than the share for all manufacturing firms and reaches 22 % of R&D conducting firms in 2001 (Table 2.11). For support-receiving firms, we explore that in the first initiation years of R&D support programs, the share of support receiving firms transferring technology is high. For the overall picture, the share of technology transferring firms in support receiving firms moves closely with R&D conducting firms' share. So, the effect of technology transferring on the probability of support receiving will be elaborated in the empirical analysis of this study.

Table 2.11. Proportion of Technology Transferring Firms, 1993-2001, (percentage)

	1993	1994	1995	1996	1997	1998	1999	2000	2001
All	1.5	1.6	1.7	1.8	1.7	1.7	1.5	1.4	1.5
R&D conducting	22.0	25.2	23.2	27.3	20.2	16.2	14.1	14.2	10.6
TTGV	80.0	50.0	41.7	27.8	21.1	14.3	6.3	11.1	21.1
TİDEB			42.3	28.8	21.9	16.5	14.7	21.1	14.1
Support receiving	80.0	50.0	44.8	28.8	23.0	17.1	15.3	21.0	14.7

Source: State Institute of Statistics

In order to compare R&D conducting and support receiving firms with all manufacturing firms, we utilized three more variables using the magnitude of R&D expenditure. We calculated the R&D intensity of firms as total R&D expenditures over total output of firm (Table 2.12.). The R&D intensity of R&D conducting firms is greater than the R&D intensity of all manufacturing firms. Moreover, the R&D intensity of R&D conducting firms has increased from 1.2 % in 1993 to 3.2 % in 2001. When we compare the R&D intensity of support receiving firms with all manufacturing firms, we see that R&D intensity of support receivers is greater than the others. The R&D intensity of support receiving firms has sharply increased after 1995 and doubled the value attained in 1993, reaching 5.8 % in 2001. We can

conclude that the R&D performance of support receiving firms is higher than other manufacturing firms.

Table 2.12. R&D Intensity by R&D status, 1993-2001, (percentage)

	1993	1994	1995	1996	1997	1998	1999	2000	2001
All	0.02	0.01	0.02	0.04	0.08	0.08	0.08	0.08	0.09
R&D conducting	1.21	0.62	0.87	1.59	2.67	2.38	2.31	2.62	3.24
TTGV	2.80	1.72	2.09	5.79	7.44	6.87	6.81	7.29	7.54
TİDEB			2.63	3.14	3.90	4.85	4.47	4.45	5.27
Support receiving	2.80	1.72	2.39	3.14	3.86	4.73	4.54	4.73	5.85

Source: State Institute of Statistics

We also calculated sectoral and regional R&D intensity of firms. The regional R&D intensity of a firm is calculated by total regional R&D expenditure of all firms over total regional output of all firms that does not include the firm itself in order to find out possible spillover effect (Table 2.13). There is no significant difference between regional R&D intensity of R&D conductors and other firms. The regional R&D intensity of R&D support receivers is slightly higher compared to that of all manufacturing firms.

Table 2.13. Regional R&D Intensity by R&D status, 1993-2001, (percentage)

	1993	1994	1995	1996	1997	1998	1999	2000	2001
All	0.17	0.14	0.14	0.20	0.22	0.30	0.46	0.39	0.40
R&D conducting	0.18	0.15	0.15	0.24	0.26	0.29	0.42	0.39	0.38
TTGV	0.17	0.14	0.16	0.19	0.27	0.32	0.50	0.49	0.35
TİDEB			0.20	0.24	0.29	0.34	0.49	0.43	0.44
Support receiving	0.17	0.14	0.20	0.24	0.29	0.34	0.49	0.42	0.43

Source: State Institute of Statistics

The sectoral R&D intensity of a firm is calculated by total sectoral R&D expenditure of all firms over total sectoral output of all firms that does not include the firm itself (Table 2.14). The sectors are identified at the level of isic4-rev.2. Contrast to regional R&D intensity of R&D conducting firms, we see that the sectoral R&D intensity of R&D conducting firms is higher than that of all firms. The value of R&D conductors' sectoral R&D intensity is 0.57 % in 2001. Moreover, the sectoral R&D intensity of R&D support receiving firms is also higher than that of all firms. We can conclude that there are sectoral spillover effects between firms conducting R&D and that firms which are more sectoral R&D intensive are in the first place to participate in R&D support programs.

Table 2.14. Sectoral R&D Intensity by R&D status, 1993-2001, (percentage)

	1993	1994	1995	1996	1997	1998	1999	2000	2001
All	0.11	0.09	0.10	0.14	0.21	0.19	0.26	0.23	0.27
R&D conducting	0.31	0.26	0.31	0.44	0.44	0.44	0.57	0.52	0.57
TTGV	0.84	0.76	1.06	0.83	0.53	0.62	0.80	0.87	1.19
TİDEB			0.83	0.68	0.60	0.75	0.94	0.66	0.86
Support receiving	0.84	0.76	0.75	0.68	0.60	0.73	0.89	0.70	0.89

Source: State Institute of Statistics

In analyzing R&D activity structures, the share of skilled employees is as important as R&D intensity giving idea about technology structure of firms. In the literature, existence of skilled employees has been perceived as one of the indicators of conducting R&D and participating in R&D support programs. In all manufacturing firms that are employing more than 10 employees, the share of skilled employees is 18 % on the average (Table 2.15). There is a difference between R&D conducting and not conducting firms in the share of skilled employees. Skilled employees constitute on the average 21 % of total employment of R&D conducting firms. R&D support receiving firms employ slightly higher skilled employees and the share of skilled employees in total employment of support receiving firms is 23 % on the average.

Table 2.15. Share of Skilled Employees by R&D status,1993-2001, (percentage)

	1993	1994	1995	1996	1997	1998	1999	2000	2001
All	17.4	18.4	17.6	17.1	16.7	17.1	18.0	17.5	18.7
R&D conducting	19.4	21.6	20.1	20.1	21.8	21.7	22.0	22.1	22.7
TTGV	25.9	22.1	26.7	24.0	23.1	24.1	24.5	26.6	29.4
TİDEB			23.1	20.0	21.3	23.9	24.4	24.0	24.5
Support receiving	25.9	22.1	22.6	20.0	21.5	24.1	24.5	23.7	24.8

Source: State Institute of Statistics

The above descriptive analysis so far gives us some evidence that there are differences between R&D conducting and not conducting firms and also between support receiving and not receiving firms. As mentioned in the aim of this study, we want to observe the effects of R&D supports on the employment generation of manufacturing firms. From this point onwards, our descriptive analysis will concentrate on displaying differences between R&D conducting and support receiving firms utilizing the data on R&D employees and their wage structure[17].

Table 2.16. Share of Full Time R&D Personnel in each occupation, 1993-2001, (percentage)

	1993	1994	1995	1996	1997	1998	1999	2000	2001
R&D conducting									
Researchers	73	74	75	78	70	67	67	70	64
Technicians	68	70	69	70	65	62	61	62	59
Supporting staff	47	56	53	51	51	42	45	53	57
Support receiving									
Researchers	83	92	86	78	71	68	69	71	66
Technicians	78	98	78	70	69	66	60	65	61
Supporting staff	52	100	75	57	51	48	45	50	57

Source: State Institute of Statistics

[17] The detailed data on R&D employees and wage payments are taken from R&D surveys conducted by SIS.

We first demonstrate the share of full time R&D personnel in each occupation[18] for R&D conducting and support receiving firms separately (Table 2.16). The share of full time personnel is calculated by working time of each occupation level multiplied by the number of employees in each occupation as a percentage divided by total number of employees in each occupation. The share of full time researchers for R&D conducting firms is on the average 71 % of total researchers employed by R&D conducting firms. However, the share of researchers employed by R&D support receiving firms and working full time is on the average 76 % which is a higher value compared to that of R&D conducting firms.

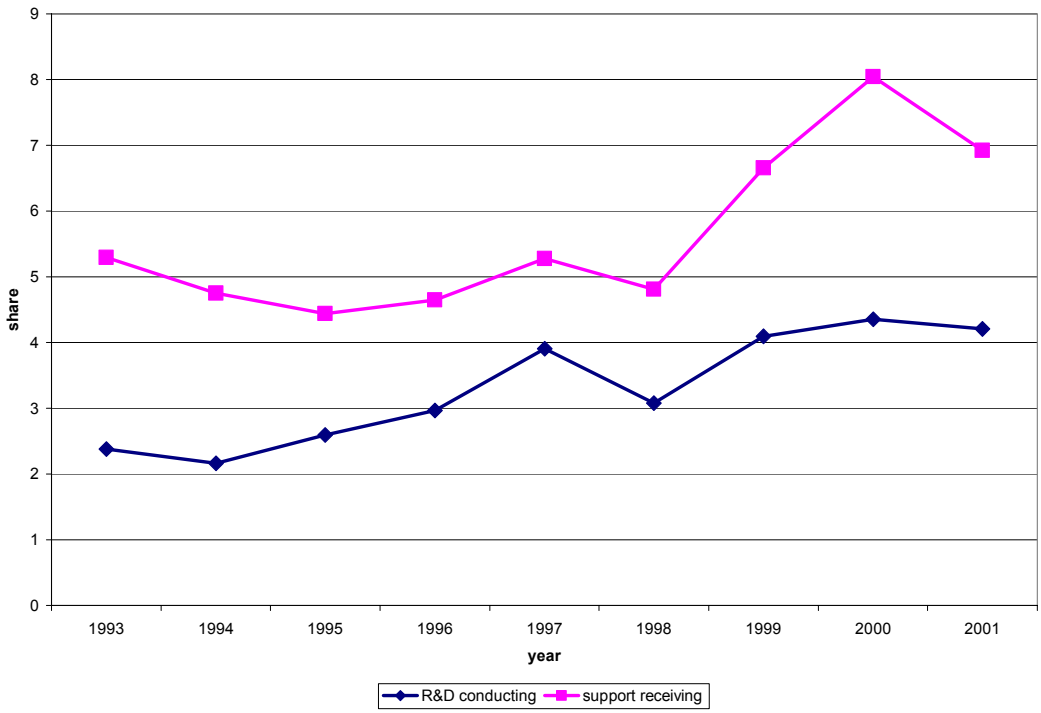

Figure 2.3. Share of R&D personnel in R&D conducting and support-receiving firms, 1993-2001, (percentage)

Source: State Institute of Statistics

[18] We classify R&D personnel by occupation into three categories as researchers, technicians and supporting staff in line with OECD Frascati Manual (2002). Researchers are professionals engaged in creation of new knowledge, products, processes and methods and also engaged in the management of the projects concerned. Technicians are persons whose main tasks require technical knowledge and experience in fields of engineering, physical and life sciences and participating in the application of concepts and operational methods. Supporting staff includes skilled and unskilled craftsmen and secretarial staff (OECD, 2002:93).

Turkish manufacturing firms that conduct R&D employ gradually more R&D personnel (Figure 2.3). The share of R&D personnel in total employment of R&D conducting firms increased 80 % and reached 4.2 % of total R&D conducting firms' employment in 2001. For support receiving firms, the increase in R&D employee generation is relatively higher than that of R&D conducting firms. R&D support receiving firms' R&D personnel employment constitutes 5.5 % of their total employment on the average. When we look at the number of R&D personnel by occupation for R&D conducting and support receiving firms separately (Table 2.17), we observe that the highest amount of R&D personnel is researchers constituting 58 % of the total R&D personnel in R&D conducting firms in 2001. The share of researchers employed in support receiving firms is also high (and slightly above the magnitudes observed for R&D conducting firms) constituting 63 % of total R&D personnel employed in 2001 by these firms. These figures nearly clarify the qualification of R&D personnel and gaining importance of researchers in Turkish manufacturing industries.

Table 2.17. Share of R&D Personnel by Occupation, 1993-2001, (percentage)

	1993	1994	1995	1996	1997	1998	1999	2000	2001
R&D conducting									
Researchers	48	54	52	51	43	54	46	49	58
Technicians	34	32	32	33	32	31	30	24	28
Supporting staff	17	14	16	16	25	15	24	26	15
Support receiving									
Researchers	72	75	62	60	49	64	51	51	61
Technicians	19	19	30	30	19	27	23	19	28
Supporting staff	9	6	8	10	32	9	26	30	12

Source: State Institute of Statistics

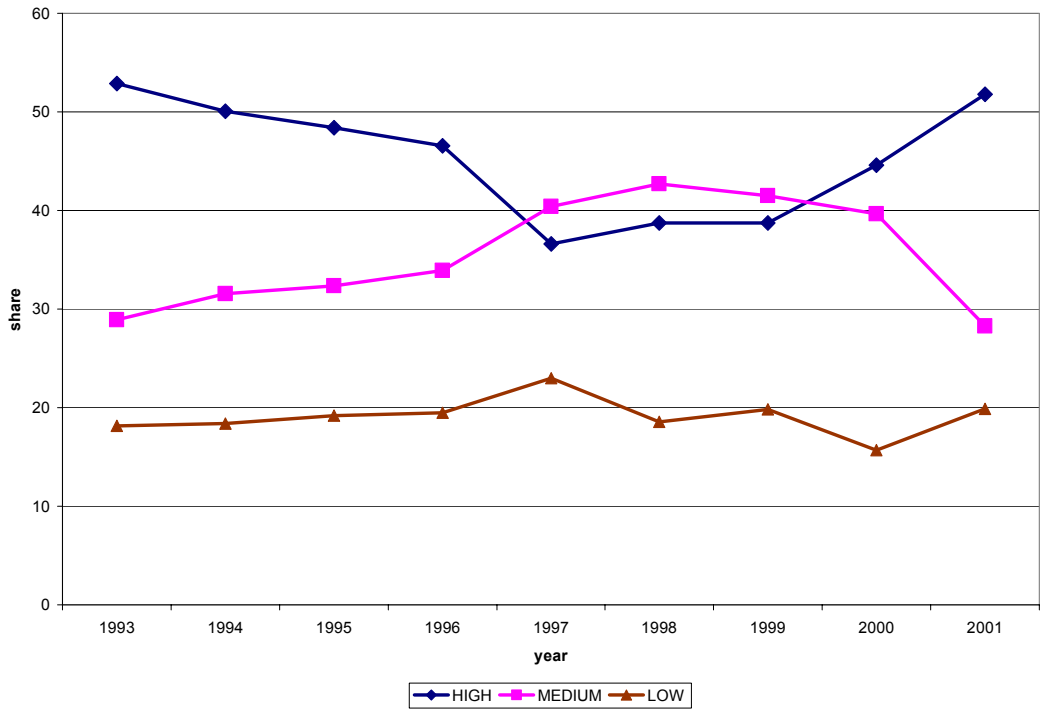

Figure 2.4. Share of Researchers in R&D Conducting Firms by Technology Level, 1993-2001, (percentage)

Source: State Institute of Statistics

By looking at the number of R&D personnel employed by R&D conducting firms and support receiving firms, we decided to restrict our analysis on researchers as they constitute the highest amount in total R&D personnel for both R&D conducting and support receiving firms, respectively. First of all, we will analyze R&D conducting firms to find out if there exists any difference between industries in their employment pattern of researcher (Figure 2.4). R&D conducting firms operating in high technology industries employ the highest number of researchers and these industries constitute nearly 50 % of total researchers employed by R&D conducting firms. However, we see a gradual increase in the share of medium technology industries and this share surpasses the share of researchers in high technology industries between years 1997-1999. The last point to be made about researcher employment pattern of R&D conducting firms is that the share of

researchers employed in high and medium technology industries constitutes 80 % of total researcher employment on the average.

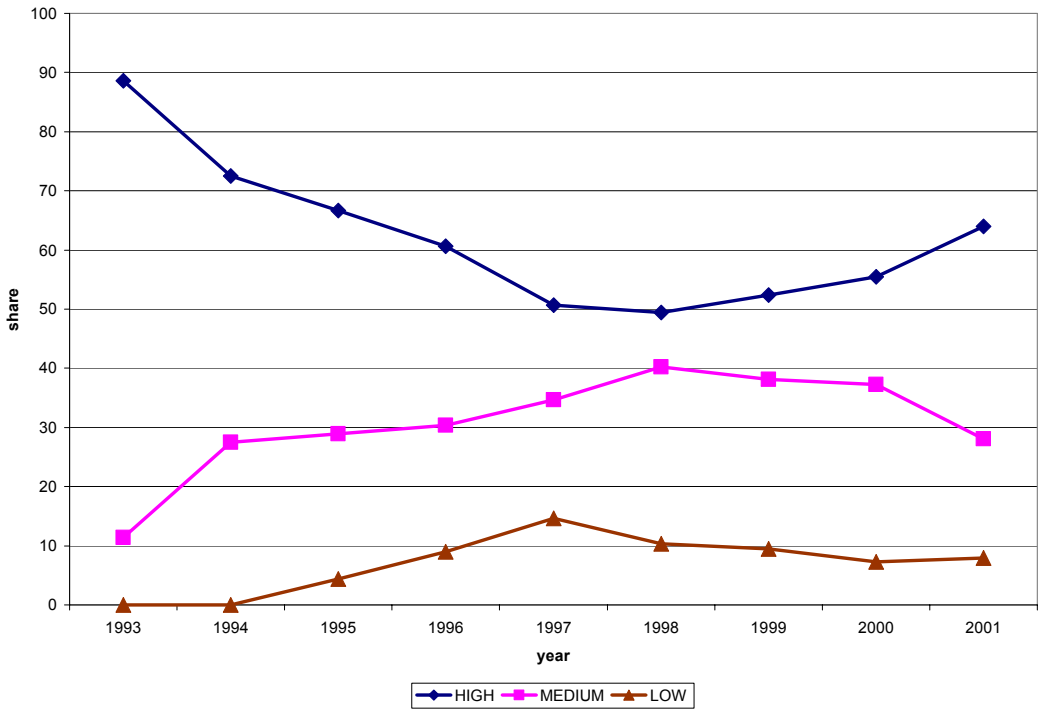

Figure 2.5. Share of Researchers in Support Receiving Firms by Technology Level, 1993-2001, (percentage)

Source: State Institute of Statistics

When we analyze support receiving firms to find out if there exists any difference between industries in their employment pattern of researcher (Figure 2.5), we see that support receiving firms operating in high technology industries employ the highest number of researchers. These industries embody nearly 90 % of total researchers employed by support receiving firms in 1993 and 64 % in 2001. Moreover, we should mention that there is a sharp decrease in the share of researchers employed by these industries. This sharp decrease in the share of high technology industries pulls up the share of medium technology industries

employing researchers. The last point to be made about researcher employment pattern of support receiving firms is that the share of researchers employed in low technology industries constitutes 10 % of total researcher employment on the average that is lower than the share observed in R&D conducting firms' employment structure.

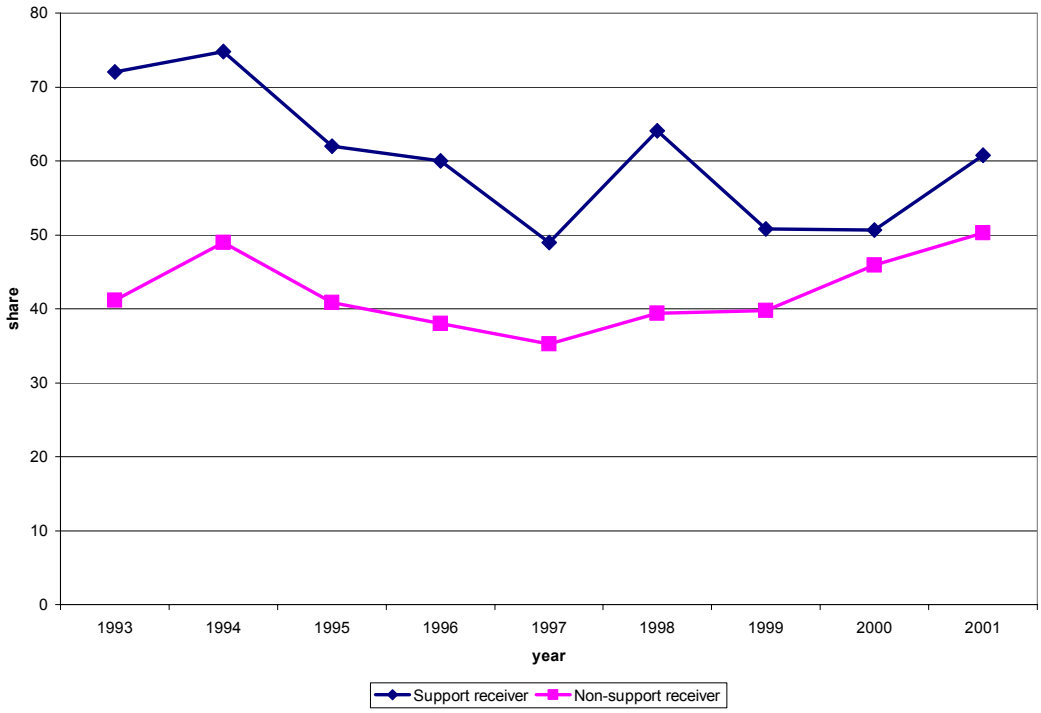

Figure 2.6. Share of Researchers by Support Receiving Status, 1993-2001, (percentage)

Source: State Institute of Statistics

We had some evidence to conclude that receiving R&D support changes the R&D personnel employment pattern of firms. In order to give exact decision on the employment effects of receiving R&D support, we displayed the share of researchers in total R&D personnel by support status of firms (Figure 2.6). We see that the share of researchers employed in total R&D personnel is nearly doubled

when firms received R&D support. The share of researchers employed by support receiving firms is 60 % on the average, whereas this share is 40 % for firms that do not receive support. *We can conclude that receiving R&D support encourages firms to increase their labor demand for researchers*.

Table 2.18. Average Wage Rate of R&D Personnel by Occupation, 1993-2001, thousand USD, PPP

	1993	1994	1995	1996	1997	1998	1999	2000	2001
R&D conducting									
Researchers	3.86	3.03	2.98	3.61	3.97	3.79	3.94	3.81	3.48
Technicians	2.25	1.67	1.64	2.04	2.15	1.87	1.98	2.11	2.21
Supporting staff	1.93	1.52	1.47	1.65	1.90	1.82	2.01	2.15	1.97
Support receiving									
Researchers	5.30	4.31	3.24	3.59	4.43	3.79	3.98	4.25	3.70
Technicians	3.70	2.31	1.86	2.14	2.32	1.99	2.09	2.29	2.22
Supporting staff	3.37	1.99	1.64	1.74	1.86	1.87	2.13	2.32	2.26

Source: State Institute of Statistics

In the literature, it is argued that the R&D support effect may be transferred to a rise in wage rate rather than an increase in the demand for R&D inputs, in our case R&D researchers. When we look at the average wage rate of researchers in R&D conducting and support receiving firms (Table 2.18), *we do not see any significant difference in the wage rates paid by R&D conducting and support receiving firms*. The average wage rate paid to researchers is the highest for both R&D conducting and support receiving firms.

The average wage rate of researchers by technology level does not bring any additional evidence on possible increase in wage paid by R&D support receiving firms (Table 2.19). The highest amount of wage paid to researchers is by firms that operate in high technology industries. In contrast, the low technology industries happen to pay the lowest wage to researchers. In the crisis years of 1994 and 1998, the amount of wage paid per R&D personnel also declines as can be seen in all macro indicators.

Table 2.19. Average Wage Rate of Researchers by Technology Level, 1993-2001, thousand USD, PPP

	1993	1994	1995	1996	1997	1998	1999	2000	2001
R&D conducting									
HIGH	4.02	3.27	3.20	3.89	3.94	3.26	3.72	3.88	3.72
MEDIUM	3.86	3.03	2.77	3.22	4.15	3.83	3.81	3.67	3.85
LOW	3.54	2.95	3.07	3.89	3.83	4.00	4.18	3.95	3.14
Support receiving									
HIGH	2.89	4.86	3.63	3.41	3.89	3.28	3.54	3.83	3.46
MEDIUM	9.00	3.19	2.89	3.02	4.70	4.07	4.25	4.44	4.26
LOW			3.28	4.91	4.43	3.74	3.97	4.31	3.10

Source: State Institute of Statistics

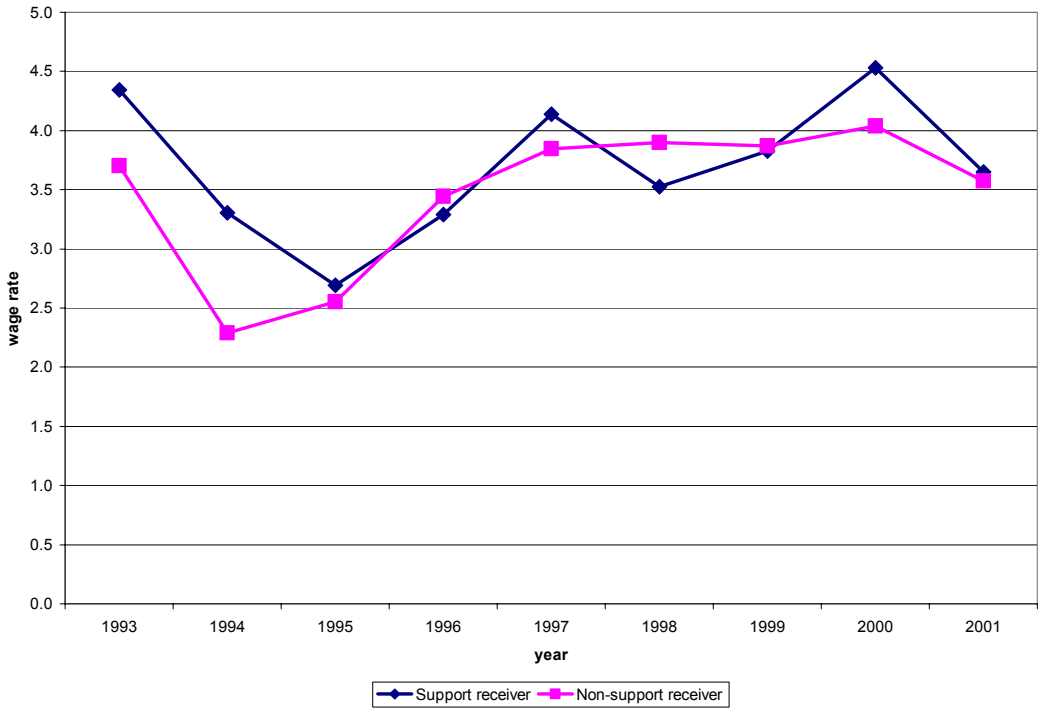

Figure 2.7. Average Wage Rate of Researchers by Support Receiving Status, 1993-2001, (percentage)

Source: State Institute of Statistics

In order to give exact decision on the wage effects of receiving R&D support, we displayed the average wage rate of researchers by support status of

firms (Figure 2.7). We see that the average wage rate of researchers paid by R&D support receiving firms move closely to the wage rate of researchers paid by firms that do not receive R&D support. The wage rate of researchers employed by support receiving firms is 3.7 on the average, whereas this rate is 3.5 for firms that do not receive support. We can conclude that receiving R&D support does not change the wage rate of researchers significantly. So, *the inference about the translation of R&D support effect to an increase in wage rate due to labor supply elasticity fails for our data*.

We dealt with various indicators for R&D conducting and support receiving firms covered by R&D surveys in the above analysis. Lastly, we will make use of extensively the data set covering TTGV and TİDEB clients and explore possible support patterns and their effect on demand for R&D researchers. Figure 2.8 displays the average number of researchers according to support patterns. We first defined a support receiver firm as receiving support from TTGV or TİDEB in any one of the years in between analyzed period. Period -2 corresponds to period labeling two years before the year that a firm received support and Period -1 labels the period that is one year before the year that the support has been received. For Period -2 and -1 firm does not receive support. Period 0 is the exact year showing that the firm receives support. Period 1 is the subsequent first year that the firm also receives support. Period 2 corresponds to period labeling one year after receiving the support and period 3 follows the same reasoning showing the second year after receiving the support. The firm receives support in Period 0 and 1 and it does not receive support in Period 2 and 3.

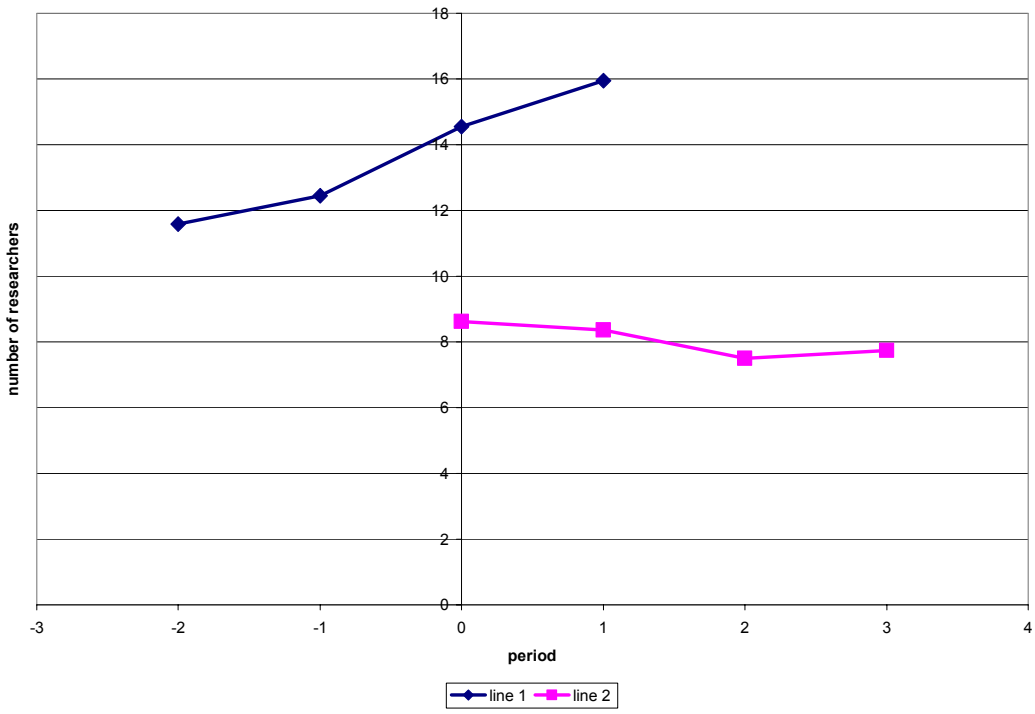

Figure 2.8. Average Number of Researchers by Support Pattern

Source: State Institute of Statistics

If we simplify our hypothetical support pattern, the first line in Figure 2.8 demonstrates the average number of researchers employed by a support receiving firm that did not receive any support for the first two periods and received support for the last two periods. This line confirms our conclusion that support receiving firms demand more researchers continuously after they received support. The second line illustrates another subsidy pattern. This firm has received support for the first two periods and did not receive support for the last two periods, which is the opposite of the first case. This second line displays that if the firm receives support for the first two periods, the average number of researchers it demands does not change significantly. However, if the same firm does not receive support for the next two periods, the average number of researchers it demands starts to decrease and the short run decrease in the number of researchers demanded seem to be larger in magnitude. We can conclude that the magnitude of demand increases will be higher if the firm receives R&D support permanently.

Table 2.20. Sectoral Number of Support Receiving Firms, 1994-2001, (percentage)

	1994	1995	1996	1997	1998	1999	2000	2001
All	1.0	1.1	1.1	1.5	2.1	2.6	3.0	3.2
R&D conducting	1.1	1.3	1.3	2.3	3.9	4.8	5.4	5.3
TTGV	1.4	1.9	1.8	2.8	5.4	8.1	6.5	9.4
TİDEB		1.6	1.5	3.0	6.0	6.9	6.8	7.5
Support receiving	1.4	1.5	1.5	3.0	5.8	6.9	6.9	7.7

Source: State Institute of Statistics

David and Hall (2000) pointed to dynamic effects of R&D supports in the literature that involves the consequences of the lagged responses of input supply and spillovers from previous results of R&D supports received. In order to check for this spillover effect, we calculated the sectoral number of support receiving firms in any year of the period 1992-2001 controlling for previous support receiving status and excluding the firm itself. The average sectoral number of support receiving firms in R&D conducting firms is continuously increasing, illustrating that there is a sectoral spillover effect for support receiving firms (Table 2.20). This sectoral spillover effect is higher in magnitude for R&D support receiving firms. The average number of support receiving firms that belong to the same sector is close to 8 in 2001 if we observe support receiving firms only.

To sum up, the number of manufacturing firms conducting R&D constitutes on the average 70 % of total number of R&D conducting firms in Turkey and 28 % of these R&D conducting firms receive R&D supports from TTGV and/or TİDEB. These support receiving firms operate dominantly in medium technology industries and they are relatively more R&D intensive. They intensively employ skilled workers and transfer technology as a source of knowledge in generating technological upgrading. When we examine the employment pattern of support receiving firms, we see that these firms continuously employ more R&D personnel (particularly in high technology industries) and the share of R&D personnel devoting their full time in production process is relatively high in support receiving firms than R&D conducting firms. A detailed analysis of the number of R&D personnel employed, lead us to restrict our analysis on researchers since they constitute the highest amount in the total number of R&D personnel employed. *We*

will conclude descriptive analysis suggesting that looking at the share of researchers in total R&D personnel by support receiving status, we see that R&D support-receiving firms employ more researchers than firms that do not receive R&D support but there is no significant evidence that these support receiving firms pay higher wage to researchers than firms that do not receive R&D support.

2.4. R&D SUPPORT AND DEMAND FOR RESEARCHERS: ECONOMETRIC ANALYSIS

2.4.1. EMPIRICAL MODEL

In order to evaluate the effects of public R&D support on labor demand of R&D personnel, we need to model first which firms are granted for R&D subsidies. In this kind of evaluation models, the observed population decomposes into subgroups, in our case firms that receive support and firms that do not receive support. However, these subgroups are not randomly emerged but are the results of a selection process, namely the selection done by granting institution. In order to give results on the effects of R&D support programs, we have to take into account the counterfactual situation that is when a support receiver firm would not have received support. If the observed data are treated as having been randomly sampled from population instead of from the subgroup of whole population associated with the selected values, potentially serious biases result. Selection models provide an appropriate econometric method taking into the account the subgroup structures of the observed data by generating an auxiliary model of process creating selected values (Hussinger, 2003:6).

The structure of sample selection models is composed of a linear regression with a binary probit selection criterion model[19]:

$$
\begin{aligned}
&y = \beta' x + \varepsilon, \\
&z^* = \alpha' w + u, \\
&\varepsilon, u \sim N\left[0, 0, \sigma_\varepsilon^2, \sigma_u^2, \rho\right].
\end{aligned}
\tag{2.2}
$$

[19] This theoretical explanation of econometric modeling, hence sample selection models will be outlined using Heckman (1979), Greene (1997) and Greene (2002).

A bivariate classical regressions model applies to the structural equations. The standard deviations are σ_ε and σ_u, and the covariance is $\rho\sigma_\varepsilon\sigma_u$. If the data were randomly sampled from this bivariate population, the parameters could be estimated by least squares, or GLS combining the two equations. However, z^* is not observed. Its observed counterpart is *z*, which is determined by

$$z = 1 \text{ if } z^* > 0 \text{ and}$$
$$z = 0 \text{ if } z^* \leq 0 .$$

Values of *y* and *x* are only observed when *z* equals 1. The essential feature of the model is that under the sampling rule, $\mathrm{E}\left[y \mid x, z = 1\right]$ is not a linear regression.

The most referred estimation approach is Heckman's approach to sample selection modeling. His approach to estimation based on the selected sample is:

$$\begin{aligned}
\mathrm{E}\left[y_i \mid x_i, z_i = 1\right] &= \mathrm{E}\left[y_i \mid x_i, \alpha' w_i + u_i > 0\right] \\
&= \beta' x_i + \mathrm{E}\left[\varepsilon_i \mid u_i > -\alpha' w_i\right] \\
&= \beta' x_i + \left(\rho\sigma_\varepsilon\sigma_u\right)\left\{\phi\left(-\alpha' w_i\right) / \left[1 - \Phi\left(-\alpha' w_i\right)\right]\right\} \\
&= \beta' x_i + \left(\rho\sigma_\varepsilon\sigma_u\right)\left[\phi\left(\alpha' w_i\right) / \Phi\left(\alpha' w_i\right)\right] .
\end{aligned} \tag{2.3}$$

Given the structure of the model and the nature of observed data, σ_u can not be estimated, so it is normalized to 1.0.Then,

$$\begin{aligned}
\mathrm{E}\left[y_i \mid x_i, z_i = 1\right] &= \beta' x_i + \left(\rho\sigma_\varepsilon\right)\lambda_i \\
&= \beta' x_i + \theta\lambda_i
\end{aligned} \tag{2.4}$$

where $\lambda(.)$ is the inverse Mill's ratio (called index function in this case), given by the bivariate normal distribution of ε_i.

In the literature survey section, we mentioned about different modeling choices of sample selection that are used in formulating the binary choice models.

The first one parametric approach, like the probit model, is the one that is based on a latent regression model in which the disturbances are assumed to have a normal distribution (Greene, 1997:874). The second one semi-parametric approach, like maximum score model, is the one that the specific distributional assumption is dropped, while the covariation of the model is retained (Greene, 1997:901). The third one non-parametric approach, like Kernel estimator, is the one that drops all the formal modeling and utilizes a bivariate modeling approach with little assumption on the probability (Greene, 1997:904).

The above outlined sample selection model can be estimated by using two estimators. The first one is Heckman's two step estimator and the second one is maximum likelihood estimator (Greene, 1997:882). Heckman's estimator is based on the method of moments. It is consistent but not an efficient estimator (Hussinger, 2003:8). However, the maximum likelihood estimators force the coefficient on index function (λ_i) to lie in the unit interval- ρ is estimated directly, not by the method of moments.

We also have to go one step further to finalize our empirical model. The specification on sample selection model that is outlined above does not take into account the model including an endogenous binary variable. A specification of the selection, known as a '*treatment effects model*' has been used in estimating models with endogeneity. This model is specified as:

$$
\begin{aligned}
&y = \beta' x + \delta z + \varepsilon \\
&z^* = \alpha' w + u \\
&z = 1 \text{ if } z^* > 0 \text{ and } z = 0 \text{ if } z^* \leq 0 .
\end{aligned}
\tag{2.5}
$$

The indicator, z is assumed to specify the presence or absence of some treatment. This is the same as the selectivity model except that z itself appears in the primary equation. Thus, there is an endogenous variable in the regression equation. The important point is that, if z is included among explanatory variables, we have to use the entire sample in our estimation.

In brief, in order to explore the problem of selection bias, we will apply *a two stage treatment effect model* where the first stage consists of estimating a probit model on the receiving probability of R&D supports. In the second stage, we

will estimate demand function for researchers including a selection term which accounts for the different propensities of firms to be publicly funded to find out the effects of R&D supports on demand for R&D employees. This selection model will treat the receipt of R&D support as endogenous by using first-step estimation on the probability to receive R&D supports. Moreover, as our data has a panel characteristic, in the second stage we will try to estimate demand function for researchers by using fixed (that is, we have group specific constant term) and random effects (that is, we have group specific disturbances) specifications[20].

The first stage of treatment effect model we applied for selection process is defined as follows:

$$\begin{aligned} SUPPORT_{i,t} &= \alpha_0 + \alpha_L \ln(L)_{i,t} + \alpha_T TTRANS_{i,t} + \alpha_S SKILLED_{it} + \alpha_C CASHF_{i,t} \\ &+ \alpha_R (RDINT)_{i,t-1} + \alpha_{SD} SECTRD + \alpha_{LR} LSUPPORTR + \alpha_{LS} LSUPPORTS \\ &+ \alpha_E ESUPPORT + \varepsilon_{i,t} \end{aligned} \tag{2.6}$$

where the subscripts i and t denote the firms ($i = 1,...,n$) and time $t = 1993 - 2001$, respectively. The dependent variable is a dummy variable taking the value 1 if firm receives support and taking the value zero otherwise (*SUPPORT*). L is the number of employees (measured in logarithmic form), *TTRANS* is a dummy variable taking the value 1 if firms transfer technology, *SKILLED* is the share of skilled personnel in total employment of firms, *CASHF* is the share of total value added minus total wage bill paid to employees over total value added utilized as a variable using profitability of firms and *RDINT* is the R&D intensity of firms[21].

The probability of receiving R&D support might be affected from existence of qualified human capital, previous experience in doing R&D, transferring technology, firm size and profitability of firms. The ability to design and implement an R&D project depends on the level of skills of employees and firm's stock of human capital (Blanes and Busom, 2004:1463). The existence of skilled employees is expected to increase the probability of receiving R&D support. The

[20] For further discussion on fixed and random effects in panel data, see Greene (1997).

[21] We calculated the price of R&D and also supported price of R&D for ever year in our data but we did not include these variables into our estimation models. Because we have time dummies and the effects of R&D prices will be offset by these time dummies if we include them into our models.

share of skilled employees in total employment is used to measure the effects of human capital on receiving support. The previous experience in doing R&D that is measured by the lagged R&D intensity of firm is expected to increase the probability of receiving R&D support (Hussinger, 2003:6).

Firm size gives an advantage at dealing both with fixed costs and with appropriating the returns of innovation. The firm size as measured by log number of employees might have a positive impact on the probability of receiving R&D support. The cost of R&D varies as a result of differences in the availability and cost of financing resources. Cash flow is a relevant variable determining the probability of receiving R&D support. Low levels of cash flow would make firms less likely to do R&D but also lead to more likely to apply to R&D support programs. However, if rationale behind R&D support programs is market failure, these failures might affect small firms relatively more. So we might have the effect of size and profitability to be negative (Blanes and Busom, 2004:1464).

We also included some other new variables into our selection model. In the descriptive analysis, we observed that the sectoral R&D intensity of support receiving firms is relatively higher in Turkey. So we added sectoral R&D intensity (*SECTRD*) of firms in our baseline model. Moreover, we observed that there are spillover effects created by R&D support receiving firms between sectors and regions. We included the number of support receiving firms that belong to the same region (*LSUPPORTR*) and the same sector (*LSUPPORTS*). The other variable added into this selection equation is *ESUPPORT* which is a dummy variable taking the value one if firm has received support previously. We expect these variables to have positive impact on the probability of support receiving due to spillover effects.

The second stage of the treatment effect model involves estimating labor demand model for researchers including the support receiving status as an explanatory variable. We will first explain a general modeling for labor demand functions. Following Nickell (1986), we start from an output production function of the form:

$$y(t) = f((N(t), z(t), t) \tag{2.7}$$

where $y(t)$ is output, $N(t)$ is employment and $z(t)$ is a vector of completely flexible inputs. We can derive a net revenue function $R(N(t),t)$ by assuming different assumptions concerning the structure of the model. For a price-taking firm, we have

$$p(t)R(N(t),t) = \max_{z(t)} \left\{ p(t)f(N(t),z(t),t) - p_z(t)z(t) \right\} \tag{2.8}$$

where $p(t)$ is the price of output, $p_z(t)$ is the vector of input prices and hence R is a function of the price ratios $p_z(t)/p(t)$.

If we have a demand constrained firm, where the output and its price are exogenous to the firm, we thus have

$$p(t)R(N(t),t) = \max_{z(t)} \left\{ p(t)y(t) - p_z(t)z(t) \mid y(t) = f(N(t),z(t),t \right\} \tag{2.9}$$

where R is now a function of $p_z(t)/p(t)$ and the exogenously determined level of output $y(t)$. It is assumed that the demand for labor is derived from profit maximizing behavior where the firm is assumed to maximize the present value of its earnings stream given by

$$PV = \sum_{t=0}^{\infty} \left(1/_{1+r_t} \right)^t \left(p(t)R(N(t),t) - w(t)N(t) - C(x(t)) \right) \tag{2.10}$$

where $C(x(t))$ is the adjustment cost function, *x(t)* satisfying $\dot{N}(t) = x(t) - \delta N(t)$ and *w(t)* is exogenously given wage, r is the discount rate. Under certain assumptions, Nickell (1986) demonstrates that in the neighborhood of equilibrium, labor demand function is described approximately by the partial adjustment equation $\dot{N}(t) = \lambda(N^* - N(t))$, where N^* is the expected equilibrium level of employment which depends on expected future prices and λ is the adjustment parameter. If it is assumed that expected future prices are forecast using past prices,

the expected equilibrium level of employment can be substituted out form the labor demand equation (Nickell, 1986:482).

The exact form of the labor demand function depends on the assumptions about i) the form of the production function, ii) the adjustment costs, iii) the structure of product and factor markets, and the behavior of the firms, and iv) expectations[22]. If the technology is homothetic, there are no adjustment costs, expectations are formed rational and all markets are perfectly competitive, then the labor demand function is reduced to a static demand function (Taymaz, 1999:20). In a static labor demand function, the current employment level is equal to the desired employment level which is determined only by current prices.

The baseline model we applied for second stage labor demand estimation can be written as follows:

$$\begin{aligned}\ln(RES)_{i,t} &= \beta_0 + \beta_R \ln(RWRES)_{i,t} + \beta_P \ln(PRINPUT)_{i,t} + \beta_W \ln(RW)_{i,t} \\ &+ \beta_S SUPPORT_{i,t} + \beta_C \ln(RPCAP)_{i,t} + \beta_Q \ln(Q)_{i,t} + \beta_T TTRANS_{i,t} + \vartheta_{i,t}\end{aligned} \tag{2.11}$$

where the subscripts i and t denote the firms ($i = 1,...,n$) and time $t = 1993 - 2001$, respectively. The dependent variable is the number of researchers in logarithmic form (*RES*). *RWRES* is the average wage rate paid to researchers, *PRINPUT* is the input price deflated by input price index, *RW* is the average real wage rate deflated by input price index, *SUPPORT* is a dummy variable taking the value 1 if the firm receives support, *RPCAP* is the real price of capital calculated from value added prices of machines and buildings and deflated by input price index, *Q* is real value of output deflated by input price index, and *TTRANS* is a dummy variable taking the value 1 if firms transfer technology. All price variables, output and number of researchers are in logarithmic form. We estimated demand for researchers with and without output so as to check for conditional demand function specification. We also included aforementioned new variables into labor demand model specification to check for spillover effects and significance of R&D intensity.

We also estimated a dynamic labor demand specification in order to see the dynamic effects of support receiving on the demand for researchers and to check

[22] For a detailed discussion on these assumptions see Hamermesh (1986) and (1993), Nickell (1986), Bresson *et al.* (1996).

for adjustment structure of labor demand. The violation of any of the assumptions listed above will lead to a dynamic labor demand equation with the adjustment term and a distributed lag in prices. The length of lag depends on the specification of the profit maximization problem and the aggregation of labor demand (Bresson *et al.*, 1996:361). Following Taymaz (1999) and Symons (1985), we will adopt an approach that is used in most of the empirical studies and very restrictive in nature[23].

The second stage dynamic labor demand model can be written as follows:

$$\begin{aligned}\ln(RES)_{i,t} &= \beta_0 + \beta_L \ln(RES)_{i,t-1} + \beta_K \ln(CSTOCK)_{i,t-1} + \beta_R \ln(RWRES)_{i,t} \\ &+\beta_P \ln(PRINPUT)_{i,t} + \beta_W \ln(RW)_{i,t} + \beta_S SUPPORT_{i,t} + \beta_C \ln(RPCAP)_{i,t} \\ &+\beta_Q \ln(Q)_{i,t} + \beta_T TTRANS_{i,t} + \vartheta_{i,t}\end{aligned} \tag{2.12}$$

where the subscripts i and t denote the firms ($i = 1,...,n$) and time $t = 1993 - 2001$, respectively. All explanatory variables have the same meaning as before. We only added lagged dependent variable and lagged capital stock (*CSTOCK*) measured by depreciation allowances over total employment as explanatory variables. We further checked for conditional labor demand specification, spillover effects and significance of R&D intensity.

2.4.2. ESTIMATION RESULTS

Table 2.21 demonstrates the effects of R&D supports on the demand for researchers in Turkish manufacturing firms for the period 1993-2001. The table is organized incorporating different model specifications and also the first panel displays selection corrected regression parameters of labor demand models whereas, the second panel displays first stage selection equation parameters. Moreover, as our data has a panel characteristic, Model 5 to Model 8 will indicate the labor demand models estimated by using fixed effects, whereas other models utilize random effects specification.

[23] Some of the examples in the empirical literature that estimated dynamic labor demand functions are Symons (1985) for Britain, Nickell (1984) and Burgess (1988) for UK, Fitzroy and Funke (1998) for Germany and Taymaz (1999) for Turkey.

The first model (Model 1) includes a baseline static labor demand model and a selection model. The probability of receiving R&D support increases with previous R&D intensity and size of the firm. As in line with Schumpeterian view, firms conducting R&D activity and receiving R&D support are large firms that can deal with fixed costs and appropriate the returns to innovation. These firms moreover, have previous experience in conducting R&D and both features lead these firms to receive R&D support to implement their R&D projects. The probability of receiving support increases with employing a higher share of skilled labor, operating in a R&D intensive sector and operating in a region and sector where the number of firms receiving R&D support is higher particularly. The cash flow does not have a significant impact on the probability of receiving support indicating that the profitability is not a selection criterion for these firms. What is interesting is that technology transfer has a negative impact on receiving R&D support (at 10 % significance level). This can be explained by the fact that the ability to transfer technology is realized as an indication of possible ability of conducting R&D regardless of receiving R&D support.

These support receiving firms further demand more researchers. The coefficient indicating the impact of R&D support receiving on the demand for researchers is 1.05. The own wage elasticity of demand for researchers is negative and -0.10 in this static model[24]. Moreover, as the price of other inputs and the average wage rate in the industry increases, firms employ more researchers. However, we observe a complementary relationship between fixed capital and researchers employed since the demand for researchers is negatively affected from the price of capital. We can conclude that capital and R&D labor is price complements (Hamermesh, 1986:433). Technology transferring firms also demand more researchers.

The second model includes output into baseline labor demand model to check for conditional demand specification. The probability of receiving R&D support in this case also increases with all of the explanatory variables except technology transfer and profitability. For the researcher demand model, all previous variables have the same sign and significance level. The coefficient

[24] The elasticities refer to short-run elasticities unless otherwise stated. In dynamic labor demand specifications, we can calculate long-run elasticities by multiplying short-run elasticities by the inverse of $(1-\beta_L)$ where β_L is the coefficient of lagged employment variable for researchers.

indicating the impact of R&D support receiving on the demand for researchers is 0.973. The own wage elasticity of researchers demand is (-0.122) in this conditional demand specification. The value of the coefficient of the output variable shows that output elasticity of researchers' employment is about 0.21.

In order to see the dynamic effects of support receiving on the demand for researchers and to check for adjustment structure of labor demand, Model 3 is estimated[25]. As in Model 2, the probability of receiving R&D support is explained with the same variables and all of the explanatory variables have the same mentioned effects on R&D support receiving probability. In dynamic labor demand model, lagged value of researchers and capital stock are included as explanatory variables. The lagged employment of researchers is positive and significant, showing sluggish employment adjustment for researchers in Turkish manufacturing firms. The coefficient of the lagged researcher employment variable is 0.77. On the other hand, we do not observe the substitution effect for input prices and complementary effect between capital and researchers employed. The coefficient indicating the impact of R&D support receiving on the researchers' demand is 0.416 showing a smaller positive effect of R&D support receiving on the demand for researchers compared to previous models. When we analyze the effect of previous support receiving and technology transferring, we still have the same positive effect of them on the demand for researchers.

Next dynamic model (Model 4) incorporates an additional output variable to obtain conditional demand parameters. The variables explaining the probability of receiving R&D support have the same signs and significance levels as in Model 3. However, the impacts of variables in the labor demand specification changes. The own price elasticity of researchers becomes significant and is -0.028. The coefficient of support receiving indicating the impact on researchers' demand is 0.428. The output elasticity of researchers' employment is about 0.094 in the short run showing that as output increases, the demand for researchers also increases. The input prices and the price of capital do not have significant impact on the demand for researchers when we included the output variable. The other point of difference from Model 3 is that the coefficient of lagged capital stock is negative

[25] We should state that dynamic modeling leads to biased results compared to static modeling theoretically.

and significant in Model 4. This demonstrates that a greater disequilibrium in the demand for capital prompts adjustment of the demand for researchers.

In order to find out if there are specification differences in our sample due to panel data formation, we estimated Model 5 which is actually static labor demand model by utilizing fixed effects panel data estimation for group specific constants. As we take into account any group specific effects, the factors determining the probability of receiving R&D support changes. The probability of receiving R&D support still increases with being R&D intensive previously. The share of skilled employees, operating in a region and sector that the number of R&D support receiving firm is high, turns out to be insignificant in determining the probability of receiving support because by applying fixed effects, we remove out all idiosyncratic firm effects. Moreover, the previous support receiving has a negative impact on the probability of support receiving indicating that R&D supports are granted without taking into account the previous support receiving status of firms.

For labor demand model, support receiving firms increase their demand for researchers as it was the case for the specifications estimated by random effects. The impact of support receiving on researchers' demand is smaller than that of previous models and the coefficient of support receiving variable equals to 0. 186. The own wage elasticity of researchers is -0.084. Different than random effect modeling, technology transfer has no significant impact on the demand for researchers. The other inputs have a complementary and the capital has substitute relation with labor input as in form of researchers.

Regarding the conditional labor demand model with fixed effects (Model 6), the probability of support receiving increases with being previously R&D intensive and operating in a R&D intensive sector, and operating in a region having a higher number of support receiving firms, whereas decreases with previous support receiving status of firms. The own wage elasticity of researchers demand is negative and -0.087. The demand for researchers increases if firm receives R&D support the same as in aforementioned models and the coefficient of support receiving variable is 0.183. The value of the coefficient of the output variable shows that output elasticity of researchers' employment is about 0.108 that is a lower magnitude that obtained from other conditional labor demand models.

In Model 7 and 8, we have a dynamic fixed effect labor demand model and conditional labor demand models respectively. In theory, the models having a lagged dependent variable will result in biased estimators with fixed effect specification. Also, the value Rho, which is utilized to decide about the specification and explanatory power of selection model, is insignificant in both cases. For Model 7, the probability of support receiving increases with firm size and lagged R&D intensity. The profitability measured by cash flow variable has a negative and significant impact on the probability of support receiving. Regarding this dynamic labor demand model, support receiving increases the demand for researchers but the own price of researchers is not significant in this case. The lagged number of researchers employed has a positive impact whereas lagged capital stock has a negative impact on the demand for researchers. For Model 8, profitability still has a negative impact on the probability of support receiving. The firm size, previous R&D intensity and technology transferring turn out to be insignificant in the selection modeling. For the labor demand specification, this model has close coefficient values and standard errors for lagged number of researchers employed and for lagged capital stock as that of Model 7. Moreover, the value of the coefficient of output variable shows that output elasticity of researchers' employment is about 0.114 indicating that as output expands, the demand for researchers also increases in this fixed effect specification.

The last model is designed to test for dynamic constant output model (Model 9). Referring Hamermesh (1993), when output variable is added, the labor demand function should be homogenous of degree zero in input prices. To be more specific, the sum of coefficients of price variables is constrained to be equal to zero. For this purpose, the price variables in Model 9 is calculated by subtracting the real price of capital from all other prices, namely the input price, own price of labor (that is the average wage rate of researchers) and average wage rate of employees. Comparing Model 4 and 9, we observe that the estimated coefficients and obtained standard errors for both labor demand models are close to each other verifying that the homogeneity of degree zero in input prices hold for dynamic labor demand specification.

In brief, our estimates of the determinants of receiving R&D support for Turkish manufacturing firms demonstrate that the size, previous R&D intensity,

share of skilled employees, sectoral R&D intensity, spillovers and dynamic effects of previous support receiving status have positive contribution in the probability of receiving R&D supports. Regarding the demand for researchers, receiving R&D support encourages firms to demand more R&D researchers. The coefficient of lagged number of researcher employment is positive showing slow-moving employment adjustment for researchers in Turkish manufacturing firms.

2.5. CONCLUSION

Although the literature provided the insights into the R&D support having stimulating impacts on private R&D expenditures and on output growth, little research has tended to focus on the relationship between labor demand and R&D supports. This study focuses on the effects of public R&D support on the demand for researchers. It departs from other studies because we focus on the effects of R&D supports on the number of R&D researchers employed by utilizing both static and dynamic labor demand modeling framework. Another point of departure from the literature is that, we explore the problem of selection bias and apply a two stage treatment effect model to define the effects of R&D support on the demand for researchers.

The recognition of the key to enhance competitive advantage in industrial enterprises through productivity improvements and hence technological innovation, started to shape Turkey's science and technology strategy and this strategy calls for adoption of systematic innovation finance programs. To fulfill this requirement, there are two institutions, TTGV and TİDEB that provide loans for industrial R&D projects. Both R&D institutions co-finance the expenditures of R&D projects carried out by industrial companies since 1992.

When we analyze the R&D activities and R&D support schemes in Turkey, we find out that the number of manufacturing firms conducting R&D constitutes on the average 70 % of total number of R&D conducting firms and 28 % of these R&D conducting firms receive R&D support from TTGV and/or TİDEB. These support receiving firms operate dominantly in medium technology industries and they are relatively more R&D intensive. They intensively employ skilled workers and transfer technology as a source of knowledge in generating technological

upgrading. When we examine the employment pattern of support receiving firms, we see that these firms continuously employ more R&D personnel (particularly in high technology industries) and the share of R&D personnel devoting their full time in production process is relatively high in support receiving firms than in R&D conducting firms. A detailed analysis of the number of R&D personnel employed leads us to restrict our analysis on researchers since they constitute the highest amount in the total number of R&D personnel employed. Our descriptive analysis advocates that R&D support-receiving firms employ more researchers than firms that do not receive R&D support but there is no significant evidence that these support receiving firms pay higher wages to researchers than firms that do not receive R&D support.

In order to test the hypothesis that receiving R&D support encourages firms to demand more researchers in Turkish manufacturing firms, we estimated a two stage treatment effect model that solves the problem of selection bias. We first explored the determinants of receiving R&D supports by using firm size, profitability, previous R&D intensity, previous support receiving status and share of skilled employee as explanatory variables. Using this sample selection based on receiving R&D support, we then estimated different labor demand specifications for researchers including support receiving as an endogenous variable by using panel data on manufacturing firms that performed R&D in the period 1993-2001. Labor demand equations include several measures of firm and technology specific indicators, such as firm size, previous support status, sectoral R&D intensity, real output, input prices, the average wage rate and technology transfer.

Our estimates of R&D support model show that size, previous R&D intensity, share of skilled employees, sectoral R&D intensity, spillovers due to operating in sectors and regions that the number of firms receiving R&D supports is high and previous support receiving status increase the probability of receiving R&D support. Regarding the demand for researchers, receiving R&D support encourages firms to demand more researchers.

Table 2.21. Effects of R&D supports on the demand for researchers, 1993-2001: Estimation Results

	Model 1 (random effects)		Model 2 (random effects)		Model 3 (random effects)		Model 4 (random effects)	
Variables	**Coeff.**	**Std.Er.**	**Coeff.**	**Std.Er.**	**Coeff.**	**Std.Er.**	**Coeff.**	**Std.Er.**
Labor demand equation								
SUPPORT	1.005	0.022 ***	0.973	0.022 ***	0.416	0.030 ***	0.428	0.030 ***
LRWRES	-0.100	0.012 ***	-0.122	0.012 ***	-0.014	0.016	-0.028	0.016 *
PRINPUT	0.107	0.050 **	0.133	0.050 ***	0.111	0.061 *	0.090	0.062
LRW	0.356	0.011 ***	0.160	0.017 ***	0.106	0.016 ***	0.037	0.022 *
RPCAP	-0.172	0.056 ***	-0.157	0.057 ***	0.103	0.029 ***	-0.072	0.071
TTRANS	0.260	0.024 ***	0.225	0.024 ***	-0.119	0.073 *	0.064	0.029 **
LQ			0.209	0.007 ***			0.094	0.009 ***
LRES_L					0.771	0.009 ***	0.733	0.009 ***
CSTOCK_L					0.002	0.008	-0.025	0.009 ***
R&D support (selection) equation								
LL	0.365	0.017 ***	0.241	0.018 ***	0.457	0.028 ***	0.411	0.027 ***
TTRANS	-0.116	0.071 *	0.018	0.070	-0.340	0.087 ***	-0.347	0.087 ***
SKILLED	0.986	0.219 ***	0.868	0.223 ***	0.910	0.332 ***	1.061	0.336 ***
CASHF	0.013	0.030	-0.009	0.026	0.042	0.083	0.044	0.064
RDINT_L	10.667	0.639 ***	9.883	0.653 ***	9.342	0.880 ***	9.341	0.884 ***
SECTRD	37.240	4.390 ***	30.090	4.019 ***	32.464	5.759 ***	29.780	5.799 ***
ESUPPORT	0.785	0.061 ***	0.640	0.064 ***	0.673	0.081 ***	0.618	0.083 ***
LSUPPORTR	0.249	0.040 ***	0.263	0.041 ***	0.222	0.055 ***	0.221	0.056 ***
LSUPPORTS	0.106	0.027 ***	0.132	0.027 ***	0.138	0.037 ***	0.127	0.037 ***
number of obs.	2679		2679		2679		2679	
Selected obs.	1861		1861		1861		1861	
Rho	-0.634	0.019 ***	-0.641	0.018 ***	-0.399	0.034 ***	-0.404	0.034 ***
F-test	2930.4 ***		2733.6 ***		2570 ***		2417.5 ***	
log likelihood	-2571		-2502		-1470		-1453	

Table 2.21. (continued) Effects of R&D supports on the demand for researchers, 1993-2001: Estimation Results

	Model 5 (fixed effects)		Model 6 (fixed effects)		Model 7 (fixed effects)		Model 8 (fixed effects)		Model 9 (random effects)	
Variables	**Coeff.**	**Std.Er.**	**Coeff.**	**Std.Er.**	**Coeff.**	**Std.Er.**	**Coeff.**	**Std.Er.**	**Coeff.**	**Std.Er.**
Labor demand equation										
SUPPORT	0.186	0.011 ***	0.183	0.006 ***	0.164	0.006 ***	0.122	0.003 ***	0.444	0.030 ***
LRWRES	-0.084	0.035 **	-0.087	0.034 ***	-0.034	0.035	-0.037	0.037	-0.029	0.016 *
PRINPUT	-0.141	Fixed **	-0.190	Fixed **	0.022	0.017	-0.008	0.020	0.086	0.059
LRW	0.062	0.059	0.048	0.057	-0.023	0.061	-0.039	0.062	0.036	0.022 *
RPCAP	0.273	0.060 ***	0.235	0.038 ***	0.194	0.036 ***	0.126	0.038 ***		
TTRANS	0.012	0.080	0.008	0.084	0.012	0.103	0.012	0.092	0.062	0.028 **
LQ			0.108	0.059 *			0.114	0.062 *	0.096	0.009 ***
LRES_L					0.164	0.055 ***	0.161	0.055 **	0.728	0.009 ***
CSTOCK_L					-0.041	0.017 **	-0.042	0.021 **	-0.025	0.009 ***
R&D support (selection) equation										
LL	-0.081	0.462	1.124	0.578	1.182	0.525 **	-0.435	0.432	0.394	0.027 ***
TTRANS	-0.385	0.276	0.420	0.321	-0.525	0.302 *	0.244	0.312	-0.298	0.085 ***
SKILLED	0.369	0.808	0.820	0.982	-1.233	1.345	1.029	1.233	0.997	0.334 ***
CASHF	-0.268	0.242	-0.527	0.388	-0.580	0.256 **	-0.544	0.312 *	0.049	0.071
RDINT_L	11.018	4.722 **	8.659	3.974 **	4.898	2.851 *	2.872	2.749	8.952	0.875 ***
SECTRD	17.800	15.993	55.779	17.676 ***	23.519	20.921	51.920	24.293 **	29.258	5.709 ***
ESUPPORT	-2.182	0.299 ***	-2.022	0.342 ***	-2.005	0.337 ***	-1.846	0.321 ***	0.646	0.081 ***
LSUPPORTR	0.204	0.181	0.491	0.190 ***	0.123	0.204	0.109	0.187	0.214	0.054 ***
LSUPPORTS	0.182	0.211	-0.381	0.262	0.143	0.202	-0.238	0.223	0.162	0.036 ***
number of obs.	2679		2679		2679		2679		2679	
Selected obs.	1861		1861		831		831		1861	
Rho	0.00004	0.00007	0.00004	1.056	-0.045	0.846 ***	-0.023	0.056 ***	-0.425	0.033 ***
F-test									2569.9 ***	
log likelihood	-7319		-24987		-9889		-4464		-1453	

Note: (***), (**), (*) means statistically significant at the 1%, 5% and 10% levels respectively and all equations include time dummies

CHAPTER III

THE DETERMINANTS OF PRODUCT AND PROCESS INNOVATIONS

3.1. INTRODUCTION

It is a common idea among economists and policy makers that the innovative capacity and the ability to imitate new technologies are key factors in determining the rate of growth of an economic system. Moreover, concern about an ongoing economic development and its major engine as technological change led to a vast literature on the identification of the economic system that is most conducive to this technological progress. The Schumpeterian definition, that technological change is one of the major determinants of industrial change and consists of introduction of new products, production processes and management methods in an economic system, has emphasized the importance of analyzing the role of innovation.

With the above definition, innovation is therefore assumed to be a highly differentiated process, specific in its scope, nature and potential impact. It has become a common practice in the literature to analyze different types of innovations that mean different outcomes in terms of economic performance, depending on the specific strategies pursued by firms and industries in the field of technological change.

This chapter focuses on the determinants of introducing innovations in Turkish manufacturing firms for the periods 1995-1997 and 1998-2000 with special emphasis on two types of innovations, namely product and process innovations. We evaluate the determinants of introducing innovations by estimating bivariate probit model that leads us to analyze the determinants of product and process innovations simultaneously. We explore the determinants of

introducing product and process innovations by using several measures of firm and industry specific characteristics such as firm size, share of skilled employee, age of the firm, R&D intensity, concentration ratio and capital intensity as explanatory variables. Going one step further, we also introduce technology specific characteristics like technology transfer, sectoral R&D intensity, internet usage intensity and as well as labor turnover and support receiving status into the traditional modeling of the determinants of introducing product and process innovations.

The outline of this chapter is as follows. The next section provides a brief discussion on the theoretical framework demonstrating the empirical evidence so far. The third section presents an overview of different types of innovations having different outcomes in terms of economic performance and analyses the characteristics of product and process innovators in Turkish manufacturing firms separately regarding the low and medium and high technology levels. The fourth section demonstrates our empirical model in order to analyze the determinants of introducing product and process innovations in Turkish manufacturing firms regarding different technology level and summarizes main empirical results from these estimations. The last section concludes this chapter by giving a brief summary of main findings.

3.2. INNOVATIVENESS: THEORETICAL FRAMEWORK

Since the mid 1980s the new growth theory has started to contemplate innovation as an engine of economic growth and developed models which include variables accounting for technology as one of the determinants of economic growth. However, the disequilibrating nature of technological change is still treated in a context assuming a general equilibrium of markets and undifferentiated economic agents (Michie *et al.*, 2002:254). A much more convincing approach in order to study the impact of innovation comprises from the start the disequilibrium nature of economic change. This view is shared by Marx and Schumpeter and more recently by neo-Schumpeterian perspectives and by evolutionary models. They all share the first postulate of Schumpeter that capitalism is an economic system

characterized above all by evolutionary turmoil associated with technological and organizational innovations.

The hypothesis suggested by Schumpeter (1942) that the large firms possessing some degree of market power is suited for the introduction of new products and new methods of production, directs the way to the first theoretical controversy on innovation, size of firm and market structure (Shrieves, 1978:329). The huge part of empirical literature on the determinants of innovativeness focuses on the two well known Schumpeterian hypotheses[26].

The first hypothesis is concerned with the relationship between firm size affecting the profitability of innovative activity and attitude to invest in innovative activities. The relative role of firm size in innovative activity has been long debated and empirically tested. Several arguments have been offered to justify the positive effect of firm size on innovative activity (Cohen and Levin, 1989:1067). One assertion is that capital market imperfections give an advantage on large firms in securing finance for R&D projects, because size is correlated with the availability of internal funding. A second assertion is that there are scale economies in the technology of R&D. Third assertion is connected with first two and states that the returns from R&D are higher when the innovator firm has a large volume of sales in order to spread the possible fixed costs of innovation. Finally, R&D is assumed to be more productive in large firms as a result of complementarities between R&D and other non manufacturing activities like marketing that may be better developed in large firms.

The above empirically ascribed advantages of large firms in innovation are associated with their relatively greater financial and technological resources. They can easily establish comprehensive external science and technology networks, able to borrow and can spread the risk over a portfolio of products, able to attract highly skilled R&D employees, able to obtain scale and learning economies through investment in production and have economies of scale and scope in R&D (Rothwell and Dodgson, 1994:310). Contradictory to those mentioned material advantages of large firms, small firms, on the other hand, have behavioral advantages. As firms grow large, efficiency in R&D is undermined through loss of

[26] Cohen and Levin (1989) review the empirical literature on the central Schumpeterian relationships between innovation, and characteristics of firms (with emphasis on firm size) and market structure.

managerial control where entrepreneurial dynamism, internal flexibility and responsiveness to changing market requirements turns out to be advantages associated with being small (Rothwell and Dodgson, 1994:311).

The most notable feature of this empirical literature on the relationship between firm size and innovation is its inconclusiveness. As stated in the survey of Cohen and Levin (1989), the evidence on the relationship between firm size and innovation in the mid-1960s was that innovative activity whether measured by input to or output of innovation, increased more than proportionally with size up to a threshold, where this relationship was either weakly negative or did not exist after. However, by mid 1980s, empirical studies showed that the outcome of the relationship between firm size and innovative activity alters with the way innovative activity measured, the method used to evaluate the relationship between firm size and innovation, the extent that industry and firm specific characteristics other than size controlled, the possible endogeneity of innovation taken into control and the possible correlation between size and other firm specific characteristics correlated with size (Cohen and Levin, 1989:1074).

The second Schumpeterian hypothesis deals with the relationship between innovation and market power and stresses the effect of concentrated market structure on innovative activity[27]. Schumpeter argues that monopolists have less financial constraints and can use their market power in order to obtain resources to devote to R&D. This is an important advantage in performing innovative activity due to R&D investments' character incorporating a lower probability of success than investment in physical capital. The empirical literature focusing on the effects of concentration on innovative behavior supported that firms in concentrated markets can more easily appropriate the returns from innovative activity and these empirical studies found a positive relationship between the two (Cohen and Levin, 1989:1075).

However, in contrast to Schumpeter, Arrow (1962) established that a firm operating in a perfectly competitive environment which gives the major incentives to innovation appears to invest more than a firm being a monopolist. The rationale behind this inference is that monopolist rents earned after the introduction of an

[27] Van Cayseele (1998) provides a survey of the theoretical contributions to the relationship between market structure and innovation.

innovation, are already warranted to him before the innovative process has occurred, but under perfect competition, it is actually the introduction of an innovation that produce all rents (Metcalfe, 1995:423). With this line of reasoning, opponents of Schumpeter's hypothesis demonstrated that gains for a firm from innovation at the margin are larger in an industry that is competitive than under monopoly conditions.

The spirit of theories relating market structure to innovative activity is a comparison of the relative incentives for innovation under the alternative regimes of competition and monopoly. However, Shrieves (1978) states that difference between these two lies in assumptions regarding the ability and conditions which an innovator's rivals can imitate new technology (Shrieves, 1978:331). This follows from the fact that an innovator has the ability to internalize the benefits from an innovation and that the net benefits to innovation are lower under monopoly since the pre-innovation profits of the monopolist represent a cost of innovation which is absent in the instance of competitive market structure. Another finding of Shrieves (1978) is that the relationship between concentration and innovative activity depends upon the kinds of market served by an industry (Shrieves, 1978:341).

Most of the above literature focuses on attributes of firms that are mostly related to innovativeness like size, liquidity and diversification. However, in seeking to understand why industries differ in the degree to which they engage in innovative activity, empirical researchers realized that the innovative process within industries is more complex than the above focuses implies. As the empirical results bearing on these hypotheses are inconclusive, there become a new growing literature on the fundamental determinants of inter-industry differences in innovation under three headings, the structure of demand, the nature and abundance of technological opportunity, and the conditions governing appropriability of the returns from innovation (Cohen and Levin, 1989:1079).

The motivation to classify the inter-industry differences with the structure of demand lead to the second theoretical controversy in the generation of innovative activity known as '*demand-pull*' versus '*technology-push*' forces of technical change. In his extensively debated work, Schmookler (1966) argued that the main stimulus to invention and innovation came from the changing pattern of

demand as measured by the investment in new capital goods in various industries (Freeman, 1994:479). He concluded that the structure of demand determined the rate and direction of innovative activity rather than the state of technological and scientific knowledge. Opponents to Schmookler's proposition stated that the sequence of particular applications of technological idea was determined not by demand but by the state of knowledge and inherent technological complexity of particular industrial applications (Cohen and Levin, 1989:1080). This '*technology push model*' describes the innovation process as entirely deriving from an exogenous advancement in scientific and technological knowledge. In this modeling, market considerations are not taken into account and there is no relation between technological change and demand. Market is seen capable of absorbing passively all of the introduced innovations.

In the empirical literature, testing for demand effects of innovative activity became important since the price elasticity of demand affecting the marginal returns to R&D investment differentiates with product and process innovations. The gains from reducing cost of production (process innovations) are larger if the demand is more elastic (Cohen and Levin, 1989:1081). On the other hand, the gains from improvement in product quality (product innovations) will be larger as the demand becomes more elastic, since inelastic demand tends to magnify the gains from a rightward shift in the demand curve.

It is widely accepted that industries differ in the opportunities they face for technical advance which brings another set of explanatory variable that is identified as technological opportunity differences. However, there is no consensus on how to make the concept of technological opportunity empirically operational (Cohen and Levin, 1989:1083). Some theoretical studies treated technological opportunity as a parameter in production function relating research resources to stock of knowledge, while others treated technological opportunity as a shift parameter determining the location of innovation possibility frontier. The most used empirical way is to represent technological opportunity as a determinant of innovative activity by classifying industries on the basis of technological orientation.

Regarding the appropriability conditions, if new knowledge is transmitted at relatively low cost from its creator to prospective competitors and if it additionally is embodied extensively in new processes and products that may be

imitated at relatively low cost, the appropriable gains will be insufficient to justify innovative activity[28] (Cohen and Levin, 1989:1091). Most of the empirical studies on appropriability has focused on the mechanisms facilitating the ability of firms to capture the returns from new technology and utilized variables observing for spillover effects.

A fundamental problem in the study of innovation and technical change is the absence of proper measures of new knowledge and its contribution to technological progress. As direct measures of innovative output are scarce, a measure of input to the innovation process, rather than a measure of innovative output is used in the empirical studies. Most commonly, innovative effort is measured by expenditures on R&D or by personnel engaged in R&D. However, a direct measure of innovation output, the number of innovations or a binary variable for firms indicating whether they introduced product or process innovations is the proper measure to be utilized. From this point onward, we will survey the determinants of introducing innovations (measured as innovative output) including industrial structure, firm characteristics, financial system, industrial relations, R&D and technology provision and the system of technology transfer that are mostly used in empirical studies.

The studies concerning the relation between firm size, market structure and innovativeness, hence testing Schumpeterian hypothesis, found that the relative innovatory roles of large and small firms can vary over the industry life cycle and there are dynamic complementarities between the technological activities of large and small firms. The most mentioned outcome of these empirical studies is that there is a U-shaped relationship between innovative activity and firm size and the same relationship applies for market structure (Rothwell and Dodgson, 1994:315).

The most referred study on the relationship between firm size and innovativeness is Acs and Audretsch (1988). They presented a model which investigates the degree to which innovative output is affected by different industry characteristics, and the extent to which small (firms with fewer than 500 employees) and large firms respond differently to various stimuli for US manufacturing firms in 1982. They assumed that innovative output is related to

[28] The recognition of this problem was also a rationale for government intervention in R&D activities due to underinvestment caused by this appropriability conditions.

innovation inducing inputs like R&D expenditures, capital intensity, firm concentration ratio, a measure of skilled labor and industry size in the previous period and found that R&D expenditures and skilled labor have positive impact and concentration ratio has negative impact on total innovative output. While skilled labor is positively associated with small-firm innovations, it has no effect on large firm innovations. Although concentration ratio is negatively associated with both large and small firm innovation, the elasticity of concentration with respect to small firm innovations is more than that for large firms (Acs and Audretsch, 1988:486).

In order to analyze the effects of market structure and size jointly, Koeller (1995) estimated a two-equation model by using the number of innovations introduced in an industry as a measure of innovativeness and try to find out the possible effects of market structure, R&D intensity, advertising intensity, capital intensity, share of skilled labor and the value of industry shipments as a control for industry size on the outcome of innovation for US manufacturing firms in 1977 and 1982. He found that industry concentration and capital intensity have negative effect whereas, R&D intensity and skilled labor force have positive effect on innovative output (Koeller, 1995:264).

An example of the empirical studies that utilizes the nature of technological opportunity and the structure of demand is Bhattacharya and Bloch (2004). They examined how firm size, market structure, profitability and growth influence innovative activity in SMEs Australian manufacturing firms for 1997 in different technological opportunity environment. They estimated the probability of firm to innovate using a probit regression technique and used firm size, profit, growth of sales, R&D intensity, concentration, export and import shares as explanatory variables. For the whole firms, they found that innovative activity increases with firm size but at a decreasing rate. The R&D intensity, market concentration, export and import shares have positive effect on innovative activity, whereas previous profitability and firm growth have no significant impact on innovative activity (Bhattacharya and Bloch, 2004:159). Regarding high-technology industries, innovative activity increases significantly with firm size, but at a decreasing rate. R&D intensity and concentration are significantly positive in influencing innovative activity. For low technology industries, innovative activity increases with firm size but at a slower rate than in high technology group. Contrary to high

technology industries, R&D intensity does not have a significant impact on innovative activity while profitability has a positive influence on subsequent innovation for firms in low technology industries (Bhattacharya and Bloch, 2004:161).

Another major determinant of innovative success lies in the nature and intensity of the interaction with contemporary and future users of an innovation. Love and Roper (1999) analyze the determinants of innovation beyond R&D by including technology transfer and networking effects, extending the standard Schumpeterian analysis (Love and Roper, 1999:43). They asserted that a linear view of the innovation process fails to allow for the possibility that innovation may come from sources which have an indirect link with any formal R&D process. This line of reasoning strengthens evolutionary models of the innovation process suggesting the importance of technology transfer as a source of technical knowledge. They found for UK manufacturing firms in 1995 that technology transfer is an important substitute for R&D in innovation process and also established that size, sales growth, regional and sectoral innovation intensity having positive and market structure having no effect on innovation (Love and Roper, 1999:55). Another study on networking relations, Harris *et al.* (2003), modeled firm's innovative status using Australian survey data 1996 to 1998. Their results indicated that large and R&D intensive firms and firms having networking relations are more likely to innovate (Harris *et al.*, 2003:685).

As the data on country specific innovative outputs have expanded, the empirical literature has shifted analysis of determinants of innovative activity by emphasizing the geographical locations and ownership structure of firms in affecting the pace of innovation. Love *et al.* (1996) analyzed the likelihood of innovation with emphasizing the role played by corporate ownership in innovation outcome of manufacturing establishments located in Scotland in 1992. They estimated a logistic regression using market share, concentration rate, firm size, R&D intensity and dummy variables controlling for corporate ownership of the firm in order to find out the probability of innovation. Their results suggested that market share and concentration ratio have no significant effect on the likelihood of innovation. Whereas, they found that the corporate structure, ownership, size and

R&D intensity have positive impact on the likelihood of innovation (Love *et al.*, 1996:741).

In order to emphasize the possible effects of geographical location and the corporate structure, Evangelista *et al.* (1997) estimated logit equations in order to observe the determinants of the probability of carrying innovative activities in Italian manufacturing firms for the period 1990-1992. They found that the probability of firm's being innovative increases monotonically with firm size and increases considerably for industrial sectors which are usually labeled by high technological opportunities. The probability of a firm's being innovative also increases if the firm is a member of an industrial group (Evangelista *et al.*, 1997:527).

Another particularly important aspect of knowledge accumulation is skill formation within firms as the combined result of formal training processes and learning by doing, using and interacting (Freeman, 1994:473). A recent study by Freel (2005) seeks to investigate patterns of association between firm-level innovativeness and a variety of skills by distinguishing between types and level of innovation for Northern British small and medium sized firms in 2001. He points out that there is a shift from highly skilled labor to low skilled labor as the innovation focus switches from product to process innovations over the industry lifecycle (Freel, 2005:124). He estimated multinominal logistic regressions of the probability of innovating controlling for age, size and skilled labor force of firm and included various dummy variables in order to check for skill requirements of firms. He found that the share of skilled labor force and size have positive impact on product innovations whereas, they do not have a significant impact on the probability of having process innovations (Freel, 2005:129). Another study, Huiban and Bouhsina (1996), analyzing the determinants of innovation propensity of the firms with special emphasis on the role of labor factor quality concluded that employing R&D personnel has positive impact on product innovations and whereas, employing technicians has a positive impact particularly on process innovations (Huiban and Bouhsina, 1996:394).

The use of personnel with high skill levels is an important factor determining the probability of engaging in innovative activity but also their mobility is a deterring factor that creates knowledge spillovers causing

underinvestment in private R&D and hence in innovative activity (Kleinknecht, 1998:394). As aforementioned, the empirical literature analyzing the conditions governing appropriability of the returns from innovation gave special emphasis to knowledge spillovers.

To best of our knowledge, Kleinknecht (1998) is the first study to analyze the relationship between labor market flexibility and innovation. Relating the consequences of restricted wage increases with lower growth rates of labor productivity since the early 1980s in The Netherlands, he concluded that policies like too modest wage increases and downward wage flexibility aiming at a greater degree of labor market flexibility may be successful in the short-run, but likely to discourage productivity growth and product innovation in the longer run since they encourage entrepreneurs to replace old vintages of capital stock with new ones slowly leading to an older and technologically less advanced capital stock (Kleinknecht, 1998:388).

Later, Michie and Sheehan (2001 and 2003) investigated the relationship between the various types of labor market flexibility and innovative activities. They tried to find out whether innovative firms have lower rates of labor turnover that is utilized as an indication of labor market flexibility using 1990's data for UK. In their first study (2001), they used a binary innovation indicator (firms that introduced at least one innovation) as a dependent variable and establishment age, labor turnover and the effects of domestic competitiveness in order to explain the likelihood of innovation (Michie and Sheehan, 2001:293). They found that high labor turnover, a high level of foreign competition and firm age are negatively correlated with the likelihood of innovation (Michie and Sheehan, 2001:300).

In their most recent study, Michie and Sheehan (2003) analyzed the effects of labor market flexibility on the probability of introducing innovation by examining the nature of innovation. They used whether the firm innovated or not and also whether the firm introduced product or process innovations as dependent variables and included the same control variables (the establishment size, dummy for foreign ownership, dummy for market share of product demand), as of those in their previous studies mentioned above. They found that being small is positively correlated with all categories of innovation, especially process innovation and being large is positively correlated with product innovation but negatively

correlated with process innovation. Age is negatively correlated with the overall probability of innovation and with product innovation, but positively correlated with process innovation. Foreign ownership, good financial performance and increase in market share are positively correlated with all categories of innovation. In relation to labor flexibility variables, high labor turnover is negatively correlated with all categories of innovation and in particular with process innovation (Michie and Sheehan, 2003:135).

A recent study by Rouvinen (2002) followed a methodology different from the ones utilized in the literature and suggested that estimation of two separate models for product and process innovations would lead to a loss of efficiency rather than estimating the two types of innovation together as they are related (Rouvinen, 2002:577). He estimated the probability of introducing product and process innovations for Finnish firms for the period 1994-1996 by using firm level variables like size and industry level variables like concentration rate. He also checked for technology push versus demand pull factors of innovation and appropriability conditions by dummy variables defining the role of customers, competitors and non profit organizations in innovation. With special emphasis to appropriability conditions, he found that they have a negative impact on likelihood of process innovations. He concluded that although the interrelations between the two types of innovation should be acknowledged, they are largely driven by different factors (Rouvinen, 2002:579).

As our study analyzes the determinants of introducing innovations by Turkish manufacturing firms, we will complete this literature survey by examining two empirical studies on Turkey. The study by Pamukçu (2003) analyzed the determinants of the decision to innovate for Turkish manufacturing firms over 1989-1993 with an emphasis on determinants that are linked to trade policy, using firm size, market structure, profits and the skill level of the labor force (Pamukçu, 2003:1447). He found that size, market structure measured as concentration, profits and skill level and trade liberalization have a positive impact on the decision to innovate (Pamukçu, 2003:1451).

The other study Taymaz (2001) analyzed the determinants of the likelihood of introducing innovation by differentiating between the types of innovation, namely product and process innovations for Turkish manufacturing firms that are

covered by Innovation Survey of SIS for the period 1995-1997. He estimated two separate logit models for product and process innovations using firm level variables like R&D intensity, number of employees, dummy for ownership, dummy for support receiving firms, dummy for belonging to a industrial group, internet usage intensity, sectoral and regional R&D intensity, dummy for technology transfer, share of skilled employees etc. and sectoral level variables like concentration ratio, export and import intensity, relative labor productivity and input R&D intensity. He found that R&D intensity and internet usage intensity have positive impact on likelihood of both product and process innovations, whereas firm size has negative impact. Firms that received R&D support and are relatively more export intensive have a higher likelihood of having process innovations, but sectoral R&D intensity has a negative impact on this likelihood. Firms that employ higher share of skilled employee have a higher likelihood of having product innovations (Taymaz, 2001:224). For variables at sectoral level, the concentration rate has a positive impact on the likelihood of product innovation. The relative labor productivity has a positive impact on product innovation likelihood whereas it has a negative impact on process innovation (Taymaz, 2001:225).

This study focuses on the determinants of introducing innovations in Turkish manufacturing firms over the periods 1995-1997 and 1998-2000. It departs from other studies because we differentiated between types of innovation as product and process innovations and utilized a different estimation method called bivariate probit models which enabled us to estimate these two innovation outcomes simultaneously.

3.3. PRODUCT AND PROCESS INNOVATIONS IN TURKISH MANUFACTURING INDUSTRY: DESCRIPTIVE ANALYSIS

An appropriate starting point to analyze the determinants of introducing innovations is the definition offered by Schumpeter (1934) himself. Innovation is defined broadly to include new products and processes, new forms of organization, new markets and the development of new skills and human capital. He defined *product innovations* as “the introduction of new good (…) or a new quality of a good” and *process innovations* as “the introduction of a new method of production

(…) or a new way of handling a commodity commercially". He also analyzed the emergence of new forms of organization, the opening of new markets and of new sources of materials.

Different types of innovations have different outcomes in terms of economic performance, depending on the specific strategies pursued by firms and industries in the field of technological change. A key distinction is between the development of process innovations introduced mainly through new investment and the product innovations based on internal innovation activities as well as on the acquisition of new intermediate or capital goods. Process innovations lead to improvements in the efficiency of production of particular goods, with savings in labor and/or capital, while product innovations increase the quality and variety of goods and may open up new markets, when the replacement of old products is not the dominant pattern within product innovations (Pianta, 2003:4).

Technologically competitive firms concentrating on product innovations tend to expand or preserve their market shares regardless of the dynamics of demand. Firms relying mainly on cost-reducing process innovations may expand production only in growing markets, while in conditions of stagnant demand they are likely to lose out to competitors new, higher quality products (Pianta, 2001:148). We can argue that a strategy focusing on product innovation follows from a search for technological competitiveness, based on high productivity rooted in quality advantages and the control of new and dynamic markets. These are typical firms at the technological frontier and are leaders in their market segments or entering new fields of activity A focus on process innovations follows from a strategy of active price competitiveness in established markets with productivity growth rooted in innovation based restructuring. This is typical of mature markets with more intense competition, and of firms adopting a follower strategy.

After a brief discussion about the distinctions between product and process innovations, we will evaluate the innovativeness of Turkish manufacturing firms. The first survey that has the proper scope in line with *Oslo Manual* regarding the innovative activity in manufacturing industries was conducted by SIS at the end of the year 1998. This survey includes the data on innovative activities conducted between 1995-1997 periods. The second survey covering innovative activities was

conducted for the period 1998-2000. These data sets are matched with the data set that covers all manufacturing firms employing more than 10 employees[29].

Table 3.1. Proportion of innovative firms by industry, 1995-1997 and 1998-2000

	1995-1997			1998-2000		
	product	**process**	**N**	**product**	**process**	**N**
Food & Agriculture Industries	0.08	0.15	2026	0.17	0.33	1854
Textile & Garment Industries	0.10	0.14	3250	0.09	0.12	4287
Wood & Wood Products	0.16	0.07	322	0.14	0.12	414
Paper & Printing Industries	0.21	0.18	237	0.09	0.20	380
Petrochemical & Chemical Industries	0.33	0.24	628	0.29	0.25	940
Stone based Industries	0.17	0.30	593	0.26	0.23	763
Iron & Steel based Industries	0.12	0.30	269	0.19	0.27	349
Non-Ferrous Metal Industries	0.23	0.25	1670	0.33	0.31	2678
Other Manufacturing Industries	0.07	0.07	4	0.19	0.10	75

Note: weighted means

Source: State Institute of Statistics

The proportion of innovative firms was 23 % for 1995-1998 and 30 % for 1998-2000. The highest proportion of innovative firms (both introducing product and/or process innovations) is observed in petrochemical & chemical industries (36 % in 1995-1997) whereas, in 1998-2000 the highest proportion of innovative firms is in non-ferrous metal industries constituting 45 % of total innovative firms[30]. However, our point of interest is the difference between product and process innovators (Table 3.1).

In the 1995-1997 period, the proportion of product innovators in petrochemical & chemical industries was 33 % and higher than the proportion of process innovators. Whereas, the proportion of process innovators was 30 % and higher than the proportion of product innovators in both stone based and iron & steel based industries which have a production technology using chemical process

[29] This matched data set also includes information regarding the support receiving status of firms.

[30] The number of firms labeled here as N has been weighted by sampling weights.

technologies. For the 1998-2000 period, the highest proportion of product innovators was in non-ferrous metal industries constituting 33 % of total product innovators and these industries also have a higher proportion than that of process innovators. For the second period, another point of distinction is that the proportion of process innovators was higher than product innovators in food & agriculture industries (33 %).

Table 3.2. Proportion of innovative firms by the type of innovation, 1995-1997 and 1998-2000

	1995-1997		1998-2000	
	Low tech	Medium & High tech	Low tech	Medium & High tech
Product innovations	0.11	0.29	0.15	0.33
Process innovations	0.16	0.29	0.20	0.28
Innovativeness(product and/or process innovations)	0.19	0.39	0.26	0.43
Product/process innovators ratio	0.83	1.15	0.73	1.11
N	1371	720	1472	866

Note: weighted means
Source: State Institute of Statistics

Table 3.2 summarizes the data on innovativeness of firms in the periods 1995-1997 and 1998-2000 for low technology and medium and high technology industries[31]. There is a clear difference between low technology and medium and high technology industries in terms of product and process innovations although the number of total innovative firms is higher in low technology industries. The proportion of firms who introduced innovations operates dominantly in medium and high technology industries and this proportion increases reaching to 43 % for the period 1998-2000. The proportion of firms introducing product and process innovations in medium and high technology industries are the same for 1995-1997 but the proportion of firms introducing product innovations increases for the period 1998-2000. Moreover, the proportion of process innovator firms operating in low

[31] Since the number of firms operating in high technology industries is small, medium and high technology industries are grouped together.

technology industries is higher than that of product innovator firms. The relative importance of product and process innovations differs in low technology and medium and high technology industries. Product/process innovators ratio is lower in low technology industries than in medium and high technology industries leading us to conclude that process innovations are more common than product innovations in low technology industries in Turkey. In other words, in low technology industries the proportion of process innovators is higher than that of product innovators and the opposite is true for product innovators that have a higher proportion in medium and high technology industries.

Table 3.3. Internet usage intensity by innovativeness, 1995-1997 and 1998-2000

	1995-1997		1998-2000	
	product	**process**	**product**	**process**
Low tech industries				
No	0.07	0.11	0.04	0.08
less than 10 %	0.21	0.30	0.17	0.23
10-24 %	0.69	0.65	0.21	0.34
25-49 %	0.35	0.30	0.33	0.44
50-74 %	1.00	0.43	0.38	0.38
75-99 %	0.91	1.00	0.38	0.47
all personnel	0.08	0.22	0.22	0.25
Medium and high tech industries				
No	0.19	0.22	0.06	0.04
less than 10 %	0.49	0.42	0.32	0.26
10-24 %	0.52	0.47	0.46	0.41
25-49 %	0.67	0.37	0.59	0.48
50-74 %	0.85	0.65	0.63	0.54
75-99 %	1.00	0.79	0.62	0.44
all personnel	0.68	0.45	0.19	0.30

Note: weighted means
Source: State Institute of Statistics

As aforementioned in the literature there may be differences between product and process innovators in their technological opportunities, R&D co-operation structures, corporate and ownership structures. One of variables

indicating the differences in technological capability of firms is the internet usage intensity that is defined as dummy variable taking different values as the proportion of employees which have direct access to the internet on the job changes (Table 3.3). In low technology industries, the proportion of process innovators that do not have any internet access at job is higher than that for the product innovators. Moreover, the share of process innovators where all personnel have access to internet is 22 % in 1995-1997 and 25 % in 1998-2000 and these values are higher than that of product innovators.

In medium and high technology industries, the share of process innovators that do not have any access to internet is relatively more than product innovators. For 1995-1997, the share of product innovator is higher if all personnel in these firms have access to internet. But in the second period, firms whose all personnel have access to internet are usually process innovators. In medium and high technology industries, as the internet usage intensity increases, the proportion of product innovators also increases. However, we can not make a similar inference about the internet usage intensity in low technology industries.

Table 3.4. R&D Co-operation, Belonging to an industrial group and Foreign ownership by innovativeness, 1995-1997 and 1998-2000

	1995-1997		1998-2000	
	product	**process**	**product**	**process**
R&D co-operation				
Low tech	0.27	0.21	0.34	0.24
Medium and high tech	0.29	0.22	0.26	0.25
Belonging to an industrial group				
Low tech	0.16	0.12	0.17	0.16
Medium and high tech	0.19	0.16	0.15	0.15
Foreign ownership				
Low tech industries	0.16	0.12	0.17	0.16
Medium and high tech	0.19	0.16	0.15	0.15

Note: weighted means

Source: State Institute of Statistics

The picture which emerges from numerous studies of innovation in firms is that the main determinant of success is the ability to make use of external sources of scientific expertise and advice (Freeman, 1994:469). For the two periods analyzed, the proportion of product innovators committing R&D co-operation is higher than process innovators (Table 3.4). Although, the proportion of R&D co-operation in medium and high technology product innovators is higher than that of process innovators in the period 1995-1997, the proportion of product innovators committing R&D co-operation and operating in low technology industries is 34 % in the period 1998-2000 which is a higher rate than previous period. This suggests that low technology firms started to commit themselves to co-operation with other actors more often than the medium and high technology ones in the period 1998-2000. Whereas, the process innovators started to commit themselves to co-operation with other actors more often than product innovators in medium and high technology industries for this second period.

The structures of foreign ownership and being a part of industrial group have similar patterns (Table 3.4). The foreign ownership and also being a part of an industrial group is higher in the product innovator firms for the two periods. But there is a shift between two periods regarding the technology orientation of firms. In 1995-1997, the medium and high technology firms introducing product innovations have a higher rate of foreign ownership and being a group firm whereas, in 1998-2000, the low technology product innovator firms have a higher rate of foreign ownership and belonging to an industrial group.

In the previous chapter, we observed that there are differences between support receiving and non-receiving firms in conducting R&D activities. This leads us to analyze the possible different impact of R&D support receiving status on introducing innovations. The share of low technology support receiving firms introducing innovations is 64 % and 81 % while, the share of low technology non-support receiving firms introducing innovations is 20 % and 26 % for periods 1995-1997 and 1998-2000 respectively. The share of medium and high technology support receiving firms introducing innovations is 83 % and 69 % whereas, the share of medium and high technology non-support receiving firms introducing innovations is 37 % and 43 % for periods 1995-1997 and 1998-2000 respectively.

These shares suggest that receiving support increases the likelihood of introducing innovations and this increase is higher in low technology firms.

Table 3.5. Support Receiving Firms by innovativeness,1995-1997 and 1998-2000

	1995-1997			1998-2000		
	product	**process**	**N**	**product**	**process**	**N**
Low tech	0.02	0.02	27	0.05	0.04	25
Medium and high tech	0.10	0.08	63	0.04	0.04	55

Note: weighted means
Source: State Institute of Statistics

When we analyzed the support receiving firms' innovativeness, the share of support receiving firms introducing product innovations is higher than that of process innovators in medium and high technology industries in the period 1995-1997 (Table 3.5). However, there is no significant difference in the share of support receiving firms introducing product and process innovations in low technology industries. Furthermore, there is no significant difference in the share of support receiving firms introducing product and process innovations in the second period. In other words, as R&D support programs spread out, the product and process innovation performance of support receiving firms approach to each other.

In order to explore the Schumpeterian hypothesis showing the relation between innovation and firm size, we classified innovative firms into size groups according to their number of employees[32] (Table 3.6). The small and medium sized (SME) firms introducing process innovations are higher for both groups of technology in the period 1995-1998. Moreover, we see a shift in SME firms' innovativeness type in the second period and these firms start to involve slightly more in introducing product innovations for both groups of technology. For low technology firms, as the size of firm increases we see that both the share of being product and process innovators decreases but the share of product innovators was

[32] The size group SME includes firms that employ less than 150 employees.

still higher than that of process innovators in low technology industries. For the second period, the share of process innovators is slightly higher than that of product innovators.

Table 3.6. Size Groups by innovativeness, 1995-1997 and 1998-2000

	1995-1997		1998-2000	
	product	**process**	**product**	**process**
Low tech industries				
SME	0.64	0.72	0.75	0.74
L>25	0.69	0.69	0.79	0.81
L>50	0.61	0.49	0.49	0.50
L>150	0.32	0.25	0.21	0.23
L>250	0.22	0.17	0.15	0.16
Medium and high tech industries				
SME	0.62	0.72	0.78	0.76
L>25	0.71	0.61	0.64	0.74
L>50	0.44	0.37	0.37	0.42
L>150	0.21	0.18	0.15	0.18
L>250	0.17	0.15	0.08	0.10

Note: weighted means

Source: State Institute of Statistics

For medium and high technology firms, as the size of firm increases we see that both the share of product and process innovators decreases but product innovators still dominate medium and high technology industries (Table 3.6). There is again an increase in the share of process innovators in medium and high technology firms in the second period but the share of firms introducing process innovations decreases as firm size increases. We can conclude that there is a negative relationship between firm size and the share of product and process innovators in Turkish manufacturing industries.

Table 3.7. Distribution of expenditures for innovation, 1995-1997 and 1998-2000

	1995-1997		1998-2000	
	product	**process**	**product**	**process**
Low tech industries				
In-house R&D	0.14	0.10	0.21	0.13
Contract R&D	0.03	0.04	0.02	0.02
Machinery & equipment	0.55	0.64	0.60	0.73
Technology transfer	0.03	0.02	0.01	0.03
Production process	0.07	0.07	0.03	0.04
Training	0.03	0.02	0.04	0.01
Marketing	0.15	0.12	0.08	0.04
Total	1.00	1.00	1.00	1.00
Medium and high tech industries				
In-house R&D	0.24	0.15	0.33	0.27
Contract R&D	0.06	0.04	0.01	0.02
Machinery & equipment	0.48	0.63	0.41	0.50
Technology transfer	0.02	0.02	0.03	0.04
Production process	0.07	0.10	0.09	0.06
Training	0.04	0.02	0.02	0.02
Marketing	0.09	0.04	0.11	0.09
Total	1.00	1.00	1.00	1.00

Note: weighted means

Source: State Institute of Statistics

The distribution of innovation expenditures over various categories of activities provides additional evidence on the differences between product and process innovators (Table 3.7). The major difference is observed in the cases of in-house R&D activities and technology embodied in machinery & equipment. The product innovators spend relatively more on in-house R&D activities than process innovators do regardless of technology orientation. In other words, building technological capabilities on the basis of in-house R&D seem to be more important for product innovator firms. Moreover, in-house R&D has a much higher share in innovation expenditures in medium and high technology industries, especially in product innovator firms: it accounts 33 % of innovation expenditures in product innovator firms in the period 1998-2000. On the other hand, the process innovators spend relatively more on technology embodied in machinery & equipment than product innovators do regardless of technology orientation. Moreover, technology embodied in machinery & equipment has a much higher share in innovation

expenditures in low technology industries, especially in process innovator firms: it accounts 73 % of innovation expenditures in process innovator firms in the period 1998-2000. Another point of interest is that marketing-related activities have a higher share in the innovation expenditure of product innovators.

Table 3.8. Proportion of R&D co-operation by innovativeness, 1995-1997 and 1998-2000

	Low tech industries				*Medium and high tech industries*			
	1995-1997		**1998-2000**		**1995-1997**		**1998-2000**	
	product	**process**	**product**	**process**	**product**	**process**	**product**	**process**
Domestic								
Own group	0.11	0.06	0.07	0.06	0.05	0.04	0.07	0.05
Users	0.14	0.08	0.12	0.11	0.05	0.04	0.09	0.08
Consultants	0.11	0.06	0.08	0.10	0.14	0.11	0.04	0.06
Suppliers	0.11	0.07	0.11	0.10	0.04	0.05	0.10	0.09
Universities/non-profit	0.18	0.13	0.10	0.09	0.10	0.07	0.16	0.14
Foreign								
Own group	0.05	0.04	0.07	0.07	0.02	0.02	0.02	0.02
Users	0.06	0.03	0.06	0.05	0.03	0.03	0.10	0.04
Consultants	0.05	0.04	0.04	0.04	0.02	0.03	0.03	0.02
Suppliers	0.11	0.08	0.06	0.06	0.04	0.04	0.05	0.04
Universities/non-profit	0.03	0.01	0.01	0.01	0.03	0.02	0.04	0.03

Note: weighted means

Source: State Institute of Statistics

Table 3.8 demonstrates the R&D co-operation of the product and process innovator firms with users, consultants, suppliers and universities and non-profit institutions. The share of product and process innovator firms for each category of co-operation listed in the table remains at the very modest levels. Furthermore, the innovator firms in Turkish manufacturing industry generally favor domestic institutions to co-operate rather than the foreign ones. The table suggests that product innovator firms commit themselves to interaction with other actors more often than process innovator firms. We also perceive that low technology firms commit themselves to R&D co-operation with other actors more often than the medium and high technology ones in the most of the categories of interaction. In

low technology industries, the product innovator firms have higher interaction with domestic users, universities plus non profit institutions and foreign suppliers in the period 1995-1997. However, the process innovator firms start to have higher interaction with domestic users and especially domestic consultants in the period 1998-2000. In medium and high technology industries, the product innovator firms have higher interaction with domestic consultants and universities plus non profit institutions in the period 1995-1997. However, the process innovator firms have a higher interaction with domestic consultants in the period 1998-2000.

Table 3.9. Knowledge sources for innovation by innovativeness, 1995-1997 and 1998-2000

	Low tech industries				*Medium and high tech industries*			
	1995-1997		**1998-2000**		**1995-1997**		**1998-2000**	
	product	**process**	**product**	**process**	**product**	**process**	**product**	**process**
Internal	2.19	2.02	2.26	2.08	2.16	1.87	2.34	2.39
Own group	0.68	0.59	0.82	0.70	0.74	0.67	0.73	0.80
Rival firms	1.77	1.68	1.57	1.89	1.39	1.19	1.62	1.86
Users	1.87	1.39	1.49	1.54	1.42	1.23	1.60	1.68
Consultants	2.30	1.72	1.84	1.67	1.85	1.78	1.81	1.82
Suppliers of capital goods	1.26	1.05	0.99	1.07	1.25	1.10	1.25	1.24
Suppliers of inputs	1.25	0.96	0.57	0.80	0.82	0.83	0.66	0.70
Suppliers of software	0.97	0.87	0.71	0.95	0.92	0.78	0.86	0.90
University	0.68	0.50	0.52	0.58	0.86	0.66	0.56	0.54
Non-profit institutions	0.45	0.35	0.25	0.39	0.66	0.56	0.49	0.53
Technology transfer	1.25	1.10	0.98	1.19	1.08	0.96	0.99	0.98
Scientific activities	1.95	1.62	1.81	1.70	1.58	1.51	1.69	1.86
Knowledge networks	1.37	1.05	1.05	1.25	1.06	0.95	1.45	1.47

Note: weighted means

Source: State Institute of Statistics

The literature emphasized both internal and external knowledge sources are important for firms in technological change process. Table 3.9 confirms this proposition: however, it also reveals that the internal knowledge of firms is still the main source for knowledge in the innovation process. Regardless of technology levels of firms, Turkish manufacturing firms rely mostly on the internal knowledge

sources for their innovative activities. Moreover, product innovators value internal knowledge sources in the innovation process more than process innovator firms do. But the process innovator firms in medium and high technology industries start to evaluate a higher value to internal knowledge sources in the period 1998-2000. The importance of consultants as a knowledge source started to diminish in low technology firms regardless of the type of innovator whereas, we observe a contrary movement in medium and high technology firms. The process innovator firms started to dedicate a higher value to rival firms and users as knowledge source, showing that rival firms appear to be a more important source of external knowledge for process innovator firms. Technology transfer which is another important source of knowledge appears to be important for process innovator firms, especially in low technology industries.

We will conclude our descriptive analysis by demonstrating some firm and sector level characteristics of product and process innovator firms (Table 3.10). As there is no clear evidence that there exist differences in firm and sector level characteristics of product and process innovator firms, we want to stress the differences between variables regarding the technology level of firms. The most notable divergence is seen in variables determining technology characteristics of firms. The R&D intensity, share of technology transferring firms, sectoral and regional R&D intensity are higher in medium and high technology industries than that of low technology industries.

For product and process innovators it is hard to verify the Schmooklers' hypothesis about market demand structure by looking at the market share of these innovator firms. The market share of product and process innovators are close to each other regardless of technology level. In order to test Schumpeters' other hypothesis related to market structure and innovation, we calculated Herfindahl index at sector level. However, there is no difference between product and process innovators regarding their market structures. Moreover, medium and high technology industries have a much more concentrated market structure than that of low technology industries.

Table 3.10. Summary Statistics by innovativeness, 1995-1997 and 1998-2000

		Low tech industries				*Medium and high tech industries*			
		1995-1997		**1998-2000**		**1995-1997**		**1998-2000**	
		product	**process**	**product**	**process**	**product**	**process**	**product**	**process**
MLL	number of employees (log)	4.29	4.12	4.09	4.15	4.09	3.86	3.86	4.00
MLTURN	labor turnover rate	0.27	0.23	0.28	0.27	0.24	0.22	0.26	0.26
MLRW	average wage rate (log)	4.29	4.27	4.69	4.69	4.66	4.55	4.87	4.95
MSKILLED	share of skilled employees	0.17	0.16	0.18	0.19	0.21	0.21	0.23	0.23
MCAPINT	capital intensity	3.76	3.64	3.88	3.84	3.70	3.55	3.60	3.83
MLQ	total output (log)	11.92	11.50	11.46	11.58	11.71	11.17	11.22	11.55
MSINPUT	subcontracted output	0.03	0.04	0.02	0.06	0.01	0.02	0.01	0.01
MSOUTPUT	subcontracted input	0.03	0.04	0.03	0.04	0.03	0.02	0.03	0.04
MFOREIGN	foreign ownership	1.38	1.49	1.88	3.28	4.75	4.31	8.44	8.29
MGROUP	group ownership	0.10	0.08	0.09	0.07	0.22	0.20	0.08	0.12
MTTRANS	technology transfer	0.02	0.02	0.06	0.05	0.07	0.06	0.04	0.05
MRDINT	R&D intensity	0.001	0.001	0.001	0.001	0.004	0.003	0.003	0.003
MREGRD	regional R&D intensity	0.002	0.002	0.004	0.004	0.002	0.002	0.005	0.005
MSECTRD	sectoral R&D intensity	0.001	0.001	0.002	0.001	0.004	0.005	0.006	0.006
MSUPPORT	support status	0.02	0.02	0.06	0.05	0.10	0.08	0.06	0.07
MSHARE	market share	0.02	0.01	0.01	0.01	0.02	0.02	0.02	0.02
MHERF	concentration ratio	0.05	0.05	0.05	0.05	0.07	0.07	0.09	0.08

Note: weighted means

Source: State Institute of Statistics

To sum up, the proportion of manufacturing firms employing more than 10 employees introducing product and/or process innovations was 23 % for 1995-1998 and 30 % for 1998-2000 and these firms dominantly operate in medium and high technology industries. *In low technology industries, the proportion of process innovators is higher than that of product innovators and the opposite is true for product innovators that have a higher proportion in medium and high technology industries.* We observed that receiving support increases the likelihood of introducing innovations and this increase is higher in low technology firms. When we analyzed the support receiving firms' innovativeness, the share of support receiving firms introducing product innovations is higher than that of process innovators in medium and high technology industries, especially in the period 1995-1997.

Regarding the relationship between firm size and innovativeness, we see that the proportion of process innovators is higher than that of product innovators in SMEs and as the size of firm increases, the share of both product and process innovators decrease. Other size groups have a higher proportion of product innovator firms and there is a negative relationship between firm size and introducing product and process innovations in Turkish manufacturing industries. The analysis of technological capabilities of Turkish manufacturing firms suggests that building technological capabilities on the basis of in-house R&D seem to be more important for product innovator firms while, the process innovators spend relatively more on technology embodied in machinery & equipment than product innovators do. Furthermore, the firms introducing innovations generally favor domestic institutions to co-operate rather than the foreign ones and the analysis regarding the type of innovation demonstrates that product innovator firms commit themselves to interaction with other actors more often than process innovator firms. Regardless of technology levels of firms, Turkish manufacturing firms rely mostly on the internal knowledge sources for their innovative activities and product innovators value internal knowledge sources in the innovation process more than process innovator firms do.

3.4. DETERMINANTS OF INTRODUCING PRODUCT AND PROCESS INNOVATIONS: ECONOMETRIC ANALYSIS

3.4.1. EMPIRICAL MODEL

In order to evaluate the determinants of introducing product and process innovations, we will utilize one of the binary choice models. In the literature, as dependent variable of introducing innovations takes binary values 0 or 1, probit model that links the probability of this outcome - taking the value of one if the firm introduces innovations and the value of zero in the opposite case- to the normal distribution is utilized as an estimation method (Greene, 1997:874). Moreover, the type of innovation (product and process) also matters to analyze the determinants of introducing innovations. Empirically, this has lead to two separate binary choice model estimation of product and process innovations. So the general empirical model becomes:

$$z_{i1} = \beta_1^{'} x_{i1} + \varepsilon_{i1} \ , \ y_{i1} = 1 \text{ if } z_{i1} > 0 \, , \ y_{i1} = 0 \text{ otherwise,} \tag{3.1}$$

$$z_{i2} = \beta_2^{'} x_{i2} + \varepsilon_{i2} \ , \ y_{i2} = 1 \text{ if } z_{i2} > 0 \, , \ y_{i2} = 0 \text{ otherwise,} \tag{3.2}$$

These two equations can each be estimated consistently by individual single equation probit methods. However, this will be insufficient if it ignores any possible correlation between the disturbances like $[\varepsilon_{i1}, \varepsilon_{i2}] \sim [0,0,1,1,\rho]$, $-1<\rho<1$ (Greene, 2001). Hence we need an extension of the probit model with correlated disturbances. The bivariate probit models are utilized in order to overcome this correlated disturbances. Moreover, for our case, there may be some interdependence between process and product innovations, in the sense that when firms introduce a new product in the market, there will be also a need to improve the production process. So, the decision to introduce product and process innovations is related and this relation is verified empirically by Leo (1996) and Rouvinen (2002) as they observed that product and process innovations have rather high and statistically significant cross-section correlations.

We have data on firms that introduce product and process innovations for the period 1995-1997 and 1997-2000. We also matched this with the data set

covering the period from 1992 to 2001 and containing data on all manufacturing firms employing more than 10 employees which is used in the first chapter. However, as the data set covering innovativeness is for the period 1995-1997 and 1998-2000, we take the arithmetic mean of all variables that are covered by manufacturing industry data set. In other words, the explanatory variables in the empirical model except for internet usage intensity that is covered by the survey of innovativeness, is measured as the mean of the variable for the period 1995-1997 and 1998-2000.

The baseline model in order to analyze the determinants of introducing product and process innovations is as follows:

$$\begin{aligned}(PRODUCT, PROCESS)_{i,t} &= \alpha_0 + \alpha_S (SKILLED)_{i,t} + \alpha_L \ln(L)_{i,t} \\ &+ \alpha_W \ln(RW)_{i,t} + \alpha_A \ln(AGE)_{i,t} + \alpha_F (FOREIGN)_{i,t} + \alpha_G (GROUP)_{i,t} \\ &+ \alpha_{RD} (RDINT)_{i,t} + \alpha_H (HERF)_{i,t} + \alpha_C (CAPINT)_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{3.3}$$

where the subscripts i and t denote the firms ($i = 1,...,n$) and time $t = 1995-1997, 1998-2000$, respectively. The dependent variable is dummy variable taking the value 1 if firm introduces a product and/or process innovation (*PRODUCT, PROCESS*) and taking the value zero otherwise. *SKILLED* is the share of skilled personnel in total employment of firms, *L* is the number of employees (measured in logarithmic form), *RW* is the average real wage rate deflated by input price index, *AGE* is the age of firms (measured in logarithmic form) , *FOREIGN* is a dummy variable taking the value 1 if the firm has a foreign owner, *GROUP* is a dummy variable taking the value 1 if the firm belongs to an industrial group, *RDINT* is the R&D intensity of firms, *HERF* is the Herfindahl index that is measured as the summation of the square of each firm's market share showing the concentration ratio and *CAPINT* is the capital intensity of firms measured by depreciation allowances over total employment.

The size variable measured as the number of employees is added to estimation model in order to check first Schumpeterian hypothesis about the relationship between firm size and innovativeness. As we mentioned in the literature, the role of firm size is expected to have a positive effect due to the

advantages of being large including financial ability, economies of scale, appropriation of returns to innovation and availability of technology resources. However, firm size and innovativeness can have a negative relationship that can be verified by small firm existence and their managerial and internal flexibility.

The concentration ratio of the firms is included to estimation model in order to check second Schumpeterian hypothesis about the relationship between market structure and innovativeness. In line with the literature, the concentrated markets are considered to appropriate the returns from innovative activity more easily and found a positive relationship between market structure and innovativeness. However, opponents of Schumpeter's hypothesis demonstrated that a firm's gains from innovation at the margin are larger in an industry that is competitive than under concentrated market conditions.

The generation of product and process innovations is also affected by the skill formation within firms that is the share of skilled employees in the total employment of firms. We expect a positive relationship between introducing innovations and existence of skilled employees. Other firm specific variables like the average wage rate, the ownership structure, belonging to an industrial group and the firm age is also added to our baseline model to test if membership in an industrial group, having foreign ownership and firm specific characteristics like age yield any positive impact on the probability of introducing innovations.

We also included R&D intensity of firms as an explanatory variable in order to determine the generation of product and process innovations. We expect a positive relationship between the two since R&D intensity is an indicator of firms' ability in conducting R&D activities. The characteristics of the production technology may also affect the probability to introduce innovations for a given stock of technological capital. Firms with more capital intensive technologies will tend to have a higher probability of introducing innovations if the rents of innovation are less threatened and high investment in capital is required (Martinez-Ros, 1999:227). It may also happen that more capital intensive processes provide less room for innovation since they are automated. We utilized intensity of capital to differentiate production technologies and to check for the effect of it on the generation of innovation.

We also included some other new variables into our baseline selection model. The first one is the market share of firms measured as the ratio of firm output to total sector output (*MSHARE*). We included market share in order to check whether demand conditions are important in the generation of innovations or not, as put forward by Schmookler (1966). The firms with more homogenous product may have more opportunities and incentives to try to introduce product innovations in order to differentiate the product. Technologically competitive firms concentrating on product innovations tend to expand or preserve their market shares regardless of the dynamics of demand. Firms relying mainly on cost-reducing process innovations may expand production only in growing markets, while in conditions of stagnant demand they are likely to lose out to competitor's new, higher quality products.

Another group of variables are included in our estimation model in order to check for whether differences in technological opportunities lead to differences in introducing product and process innovations. We added sectoral R&D intensity (*SECTRD*) of firms in order to capture the R&D spillovers from other firms. Another major determinant of innovative success stated by Love and Roper (1999) lies in the nature and intensity of the interaction with contemporary and future users of an innovation. We included technology transfer (*TTRANS*) in to our analysis to check for a possible networking relation. In order to differentiate between technological opportunities of firms, we utilized the internet intensity (*INTERINT*) measured as the proportion of employees who have direct access to the internet on the job. If the generation of innovation requires extensive exchange of information and regarding the internet as one of the basis of information, this variable is expected to have a positive coefficient in the probability of introducing product and process innovations.

In line with Michie and Sheehan (2001 and 2003), we try to investigate the relationship between labor market flexibility and innovative activities. We utilized labor turnover (*LTURN*) measured as the ratio of the sum of the number of employees who left the firm in a year and who was hired by the firm in a year to the average number of employees (average employment plus the number of employees who were hired and fired by the firm in a year). High labor turnover is

expected to be negatively correlated with introducing all types of innovation and in particular with the process innovations.

The effects of subcontracting relations on the generation of product and process innovations are tested by using two variables, the share of subcontracted inputs in total inputs (*SINPUT*) and the share of subcontracted by other firms in total output (*SOUTPUT*). These variables are utilized to check if subcontract-receiving and subcontract-offering firms have higher probability to introduce product and process innovations.

Finally, having discussed the positive impact of receiving R&D support in conducting R&D activities, we want to test the impact of receiving R&D support on the introduction of product and process innovations (*SUPPORT*). The most important input of innovations is R&D activities and receiving R&D support has a direct positive impact on R&D activities via increases in R&D intensity and may have an indirect impact on the probability of introducing innovations leading to higher efficiency in R&D activities (Taymaz, 2001:220).

3.4.2. ESTIMATION RESULTS

Table 3.11 and Table 3.12 demonstrate the determinants of introducing product and process innovations for low technology Turkish manufacturing firms in the period 1995-1997 and 1998-2000 respectively. Before going into detail, utilizing a bivariate probit estimation method for different type of innovations is efficient, since the log likelihood ratio test for Rho being equal to 0 is rejected leading us to conclude that product and process innovations have correlated disturbances.

Model 1 is used to determine the variables affecting the introduction of product and process innovations and includes the share of skilled employees, size, average wage rate, firm age, dummy for foreign ownership and belonging to an industrial group, R&D intensity, concentration ratio and capital intensity of firms as explanatory variables. The introduction of product innovations is not affected from the skill composition of employees, whereas the introduction of process innovations is positively affected by the share of skilled employees in low technology firms. Both the introduction of product and process innovations in low

technology firms increases with firm age, being R&D intensive and capital intensive, whereas decreases with the average wage rate of firms. The foreign ownership has a negative impact on the probability of introducing product innovations whereas it has a positive impact on the probability of introducing process innovations. Furthermore, belonging to an industrial group has a positive impact in the probability of introducing product innovations in low technology industries since low technology firms will have a higher opportunity to innovate if they have a relationship with a foreign firm.

For the relationship between firm size, market structure and innovativeness, the probability of introducing product and process innovations both increase with firm size and concentration ratio. In other words, the probability of introducing innovations regardless of the type is higher in large firms operating in concentrated markets in low technology industries. This conclusion can be verified by the fact that only large and oligopolistic firms will have a higher opportunity to engage in innovative activity since small firms in these industries will have additional disadvantages due to being in low technology industries. Also, the proposition of large firms having higher probability of introducing innovations in low technology industries can be explained due to scale effects. Moreover, the coefficient of concentration ratio for the product innovation is more than that of process innovation and the coefficient of size for the process innovation is more than that of product innovation. This may suggest that being large is relatively more important in introducing process innovations whereas concentrated market structure is relatively more important in introducing product innovations since product differentiation is important for competition in concentrated market structures.

Model 2 includes the market share variable in order to test the effects of market demand on the generation of product and process innovations. In low technology industries, the probability of introducing innovations regardless of the type is not affected from the demand structure. This finding is similar to that of Bhattacharya and Bloch (2004). This is contradictory to our expectations since the driving force of innovation in low technology industries is usually explained by demand pull forces of technological change. The other explanatory variables have the same signs and significance levels as in previous model.

Model 3 tests for firm specific technological opportunities in determining the generation of innovations. When we included these new variables, all other explanatory variables except R&D intensity have the same effects. But, R&D intensity becomes insignificant in affecting the probability of introducing product and process innovations. This may be due to the fact that especially technology transfer can be a substitute to in-house R&D conducting. The probability of introducing both product and process innovation increases with the ability to transfer technology, operating in R&D intensive sector and having higher internet intensity. Moreover, technology transferring seems to be more important in introducing product innovations.

The next model (Model 4) incorporates labor turnover and the subcontracting relations into previous models. The labor turnover has a positive impact on the probability of introducing product innovations while it has no significant impact on the probability of introducing process innovation in low technology industries. This is a contradictory finding to that of Michie and Sheehan (2001 and 2003). This outcome can be explained by the fact that labor turnover in low technology industries is dominated by the number of employees fired due to low skill levels. For subcontracted output and input relations, we find that they have a negative contribution on the probability of introducing product innovations and have no impact on process innovations.

The last model for low technology industries (Model 5) tests for the effects of support receiving on introducing product and process innovations. All other variables have the same signs and significance levels except R&D intensity in product innovations and technology transfer in process innovations. The R&D intensity of firms does not have any significant effect on the probability of introducing product innovations like in Model 3 and 4. The positive effect of technology transferring on the probability of introducing process innovations turned out to be insignificant when we included support variable. Although receiving R&D support has a positive impact both on the probability of introducing product and process innovations, this positive impact is only significant in process innovations. This outcome is in line with our previous findings that low technology industries introduce relatively more process innovations than that of product innovations.

Table 3.13 and Table 3.14 demonstrate the determinants of introducing product and process innovations for medium and high technology Turkish manufacturing firms in the period 1995-1997 and 1998-2000 respectively. All of the models have the same explanatory variables like the ones introduced in low technology industries. For Model 1, unlike the results we obtained in low technology industries, the probability of introducing innovations regardless of the type is positively affected from employing a higher share of skilled employees in medium and high technology industries. Both the generation of product and process innovations in medium and high technology firms increases with firm age, being R&D intensive and capital intensive, whereas decreases with the average wage rate of firms. In other words, the effects of firm age, being R&D intensive and capital intensive and the average wage rate does not change with the type of innovation and technology level.

Different than low technology industries, the foreign ownership has a positive impact on generation of innovation regardless of the type of innovation. Another point of divergence is that belonging to an industrial group has a positive impact on the probability of introducing process innovations in high technology industries, opposite of the case we observed in low technology industries. This can be due to the fact that in medium and high technology industries, firms attain the process innovations from their mother firm.

For the relationship between firm size, market structure and innovativeness, the probability of introducing product and process innovations both increase with firm size in medium and high technology industries. In other words, the probability of introducing innovations is higher in large firms having the advantage of economies of scale and financing opportunities, regardless of the type of innovation and technology level. However, we perceive a different picture for the market structure. The probability of introducing product innovations is higher in concentrated markets which is the same outcome attained for low technology firms. But, the probability of introducing process innovations decreases as the market structure becomes concentrated. This outcome can be explained by referring to Schrieves (1978). He has shown that, in the case of process innovation, the competitive organizational form will lead to a greater incentive for allocation of

resources to incentive activity than would monopolistic structure of the industry (Schrieves, 1978:332).

Although the market share variable does not have a significant impact on the probability of introducing innovations in low technology industries, the market share has a positive impact on the generation of process innovations in medium and high technology industries. In medium and high technology industries, there may be a focus on process innovations following from a strategy of active price competitiveness in established markets with productivity growth rooted in innovation based restructuring. So, as the market share of these firms increases, they compete by introducing more process innovations. Regarding the other explanatory variables, they have the same signs and significance levels as in previous model.

Model 3 tests for firm specific technological opportunities in determining the generation of innovations in medium and high technology industries. When we included these new variables, R&D intensity became insignificant in affecting the generation of product and process innovations in low technology industries. However, for medium and high technology industries, being R&D intensive increases the probability of introducing product and process innovations. Technology transfer used to have a positive impact on the probability of introducing innovations in low technology industries. In medium and high technology industries, technology transfer has a negative impact on the generation of both process and product innovations. This can verified with our findings in descriptive analysis that technology transfer is an important source of knowledge especially in low technology industries and that medium and high technology industries evaluates a higher value to internal knowledge sources. The probability of introducing both product and process innovation still increases with having higher internet intensity but sectoral R&D intensity does not have a significant impact for medium and high technology industries. In other words, R&D spillovers from other firms are relatively more important for low technology firms than that of medium and high technology ones.

The next model (Model 4) incorporates labor turnover and the subcontracting relations into the previous models. Contrary to the low technology industries, the labor turnover has a negative impact on the probability of

introducing process innovation in medium and high technology industries. This finding was stated by Kleinknecht (1998) and supported by the fact that the labor mobility creates knowledge spillovers and these spillovers may cause underinvestment in private R&D and hence in innovative activity. For subcontracted output and input relations, we find that subcontracted output has a negative impact on the generation of innovations regardless of the type while, subcontracted input has a positive impact on the generation of process innovations.

The last model for medium and high technology industries (Model 5) tests for the effects of support receiving on the probability of introducing product and process innovations. All other variables have the same signs and significance levels except R&D intensity in process innovations. The R&D intensity of firms does not have any significant impact on generation of process innovations that is a different outcome than that of previous models in medium and high technology industries. Although receiving R&D support has a positive impact both on the probability of introducing product and process innovations, this positive impact is only significant in product innovations. This is also another point of divergence between low and medium and high technology industries. This outcome is similar to our previous finding that the share of support receiving firms introducing product innovations is higher than that of process innovators in medium and high technology industries.

To sum up, *the determinants of introducing product and process innovations seem to be related but vary with the technological orientation of the industry*. The generation of innovations regardless of the type is positively affected from employing a higher share of skilled employees in medium and high technology industries, whereas skilled employees do not have any contribution in low technology industries. The positive effect of firm age, being R&D and capital intensive and negative effect of the average wage rate does not change with the type of innovation and technology level.

For the relationship between firm size, market structure and innovativeness, the probability of introducing innovations is higher in large firms having the advantage of economies of scale and financing opportunities, regardless of the type of innovation and technology level. Regarding the market structure, the probability of introducing product innovations is higher in concentrated markets which is the same outcome that of low technology firms. But, the probability of introducing

process innovations decreases as the market structure becomes concentrated in medium and high technology industries.

Although the market share variable does not have a significant impact on the probability of introducing innovations in low technology industries, the market share has a positive impact on the probability of introducing process innovations in medium and high technology industries. This leads us to conclude that medium and high technology firms in Turkey focuses on introducing process innovations following from a strategy of active price competitiveness.

Technology transfer has a positive impact on the probability of introducing innovations in low technology industries while, it has a negative impact on the probability of introducing innovations in medium and high technology industries. This is inline with our findings in descriptive analysis that technology transfer is an important source of knowledge especially in low technology industries and that medium and high technology industries evaluates a higher value to internal knowledge sources. Moreover, R&D spillovers from other firms are relatively more important for low technology firms than that of medium and high technology ones. The proportion of employees who have direct access to the internet on the job, namely internet intensity has a positive impact on the probability of introducing both product and process innovations regardless of the technology level, leading us to conclude that the internet access is regarded as one of the basis of information by Turkish manufacturing firms.

Contrary to the low technology industries, the labor turnover has a negative impact on the probability of introducing process innovation in medium and high technology industries. In medium and high technology industries, labor market flexibility measured by labor turnover cause underinvestment in private R&D and hence in innovative activity. Regarding the support receiving status, although receiving R&D support has a positive impact both on the probability of introducing product and process innovations regardless of technology level, this positive impact is only significant in product innovations in medium and high technology industries and in process innovations in low technology industries. This outcome is in line with our previous finding that the share of support receiving firms introducing product innovations is higher than that of process innovators in medium and high technology industries.

3.5. CONCLUSION

The Schumpeterian hypothesis that technological change is the main determinants of industrial change and consists of the introduction of new products, production processes and management methods in an economic system points the fact that different types of innovations have different outcomes in terms of economic performance. This chapter is focused on the determinants of introducing innovations in Turkish manufacturing firms for the periods 1995-1997 and 1998-2000 with special emphasis given to two types of innovations: product and process innovations. It departs from other studies because we differentiated between types of innovation as product and process innovations and utilized a different estimation method called bivariate probit models which enabled us to estimate these two innovation outcomes simultaneously.

The analysis regarding the characteristics of product and process innovators in Turkish manufacturing industries show that the proportion of manufacturing firms employing more than 10 employees introducing product and/or process innovations was 23 % for 1995-1998 and 30 % for 1998-2000 and these firms dominantly operate in medium and high technology industries. In low technology industries, the proportion of process innovators is higher than that of product innovators and the opposite is true for product innovators that have a higher proportion in medium and high technology industries. We observed that receiving support increases the likelihood of introducing innovations and this increase is higher in low technology firms. When we analyzed the support receiving firms' innovativeness, the share of support receiving firms introducing product innovations is higher than that of process innovators in medium and high technology industries, especially in the period 1995-1997.

For the relationship between firm size and innovativeness, we see that the proportion of process innovators is higher than that of product innovators in SMEs. Other size groups have a higher proportion of product innovator firms and there is a negative relationship between firm size and the share of product and process innovators in Turkish manufacturing industries. The analysis of technological capabilities of Turkish manufacturing firms suggests that building technological capabilities on the basis of in-house R&D seem to be more important for product

innovator firms while, the process innovators spend relatively more on technology embodied in machinery & equipment than product innovators do. Regardless of technology levels of firms, Turkish manufacturing firms rely mostly on the internal knowledge sources for their innovative activities and product innovators value internal knowledge sources in the innovation process more than process innovator firms do.

In line with the outcomes of our descriptive analysis indicating that the existing differences between product and process innovators stem from technological orientation of the industry, we estimate bivariate probit model that leads us to analyze the determinants of introducing product and process innovations simultaneously. We explore the determinants of introducing innovations by using several measures of firm and industry specific characteristics such as firm size, share of skilled employee, age of the firm, R&D intensity, concentration ratio and capital intensity that also helps us to test traditional Schumpeterian hypothesis. Going one step further, we also introduce technology specific characteristics like technology transfer, sectoral R&D intensity, internet usage intensity and in addition labor turnover and support receiving status into this traditional modeling of the probability of introducing product and process innovations.

The estimation results verified that the determinants of introducing product and process innovations vary with different technology orientations. The probability of introducing innovations regardless of the type is positively affected from employing a higher share of skilled employees in medium and high technology industries, whereas skilled employees do not have any contribution in low technology industries. The positive effect of firm age, being R&D and capital intensive and negative effect of the average wage rate does not change with the type of innovation and technology level.

For the relationship between firm size, market structure and innovativeness, we observe that the probability of introducing innovations is higher in large firms having the advantage of economies of scale and financing opportunities, regardless of the type of innovation and technology level. Regarding the market structure, the probability of introducing product innovations is higher in concentrated markets which is the same outcome that of low technology firms. But, the probability of

introducing process innovations decreases as the market structure becomes concentrated in medium and high technology industries.

Although the market share variable does not have a significant impact on the probability of introducing innovations in low technology industries, the market share has a positive impact on the probability of introducing process innovations in medium and high technology industries. This leads us to conclude that medium and high technology firms in Turkey focuses on introducing process innovations following from a strategy of active price competitiveness.

Technology transfer has a positive impact on the probability of introducing innovations in low technology industries while, it has a negative impact on the probability of introducing innovations in medium and high technology industries. This can verified with our findings in descriptive analysis that technology transfer is an important source of knowledge especially in low technology industries and that medium and high technology industries evaluates a higher value to internal knowledge sources. Moreover, R&D spillovers from other firms are relatively more important for low technology firms than that of medium and high technology ones. The proportion of employees who have direct access to the internet on the job, namely internet usage intensity has a positive impact on the probability of introducing both product and process innovations regardless of the technology level, leading us to conclude that the internet access is regarded as one of the basis of information by Turkish manufacturing firms.

Contrary to the low technology industries, the labor turnover has a negative impact on the probability of introducing process innovation in medium and high technology industries. In medium and high technology industries, labor market flexibility measured by labor turnover cause underinvestment in private R&D and hence in innovative activity. Regarding the support receiving status, although receiving R&D support has a positive impact both on the probability of introducing product and process innovations regardless of technology level, this positive impact is only significant in product innovations in medium and high technology industries while is only significant in process innovations in low technology industries. This outcome is in line with our previous finding that the share of support receiving firms introducing product innovations is higher than that of process innovators in medium and high technology industries.

Table 3.11. The determinants of introducing product innovations: Estimation Results for Low Technology Industries 1995-1997 and 1998-2000

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
MSKILLED	0.108	0.126	0.110	0.126	0.121	0.129	0.187	0.130	0.187	0.130
MLL	0.102	0.014 ***	0.096	0.014 ***	0.086	0.015 ***	0.093	0.015 ***	0.092	0.015 ***
MLRW	-0.056	0.027 **	-0.058	0.027 **	-0.203	0.029 ***	-0.197	0.030 ***	-0.196	0.030 ***
LNAGE	0.091	0.018 ***	0.090	0.018 ***	0.108	0.019 ***	0.079	0.019 ***	0.079	0.019 ***
MFOREIGN	-0.004	0.001 ***	-0.004	0.001 ***	-0.006	0.002 ***	-0.005	0.002 ***	-0.005	0.002 ***
MGROUP	0.245	0.066 ***	0.241	0.066 ***	0.208	0.068 ***	0.191	0.069 ***	0.188	0.069 ***
MRDINT	9.672	1.959 ***	9.752	1.959 ***	2.321	2.220	2.770	2.172	1.689	2.393
MHERF	2.712	0.302 ***	2.515	0.328 ***	1.392	0.354 ***	0.928	0.361 ***	0.952	0.361 ***
MCAPINT	0.270	0.011 ***	0.268	0.012 ***	0.220	0.012 ***	0.216	0.012 ***	0.216	0.012 ***
MMSHARE			0.940	0.636	2.021	0.674 ***	1.829	0.676 ***	1.799	0.677 ***
MTTRANS					0.445	0.148 ***	0.416	0.147 ***	0.404	0.147 ***
MSECTRD					153.759	12.511 ***	141.145	12.399 ***	138.276	12.550 ***
INTERINT					0.218	0.011 ***	0.225	0.011 ***	0.226	0.011 ***
MLTURN							0.242	0.075 ***	0.243	0.075 ***
MSINPUT							-1.255	0.188 ***	-1.257	0.188 ***
MSOUTPUT							-0.771	0.107 ***	-0.772	0.108 ***
MSUPPORT									0.155	0.154
CONSTANT	-2.568	0.102 ***	-2.518	0.107 ***	-2.008	0.113 ***	-1.939	0.118 ***	-1.936	0.119 ***

Table 3.12. The determinants of introducing process innovations: Estimation Results for Low Technology Industries 1995-1997 and 1998-2000

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
MSKILLED	0.611	0.109 ***	0.611	0.109 ***	0.631	0.111 ***	0.627	0.111 ***	0.622	0.111 ***
MLL	0.136	0.013 ***	0.142	0.013 ***	0.131	0.014 ***	0.133	0.014 ***	0.129	0.014 ***
MLRW	-0.134	0.025 ***	-0.132	0.025 ***	-0.243	0.027 ***	-0.244	0.027 ***	-0.242	0.027 ***
LNAGE	0.218	0.017 ***	0.219	0.017 ***	0.247	0.018 ***	0.247	0.018 ***	0.246	0.018 ***
MFOREIGN	0.003	0.001 ***	0.003	0.001 ***	0.003	0.001 ***	0.003	0.001 ***	0.003	0.001 ***
MGROUP	0.008	0.064	0.013	0.064	-0.032	0.066	-0.032	0.066	-0.044	0.066
MRDINT	7.435	2.059 ***	7.371	2.062 ***	1.502	2.268	1.379	2.305	-2.758	2.723
MHERF	2.156	0.284 ***	2.326	0.308 ***	1.687	0.326 ***	1.660	0.332 ***	1.732	0.334 ***
MCAPINT	0.269	0.010 ***	0.271	0.011 ***	0.229	0.011 ***	0.229	0.011 ***	0.228	0.011 ***
MMSHARE			-0.866	0.617	-0.275	0.644	-0.309	0.644	-0.427	0.646
MTTRANS					0.282	0.139 **	0.282	0.139 **	0.261	0.142
MSECTRD					96.092	10.784 ***	96.405	10.839 ***	89.175	11.592 ***
INTERINT					0.196	0.011 ***	0.198	0.011 ***	0.198	0.011 ***
MLTURN							-0.083	0.068	-0.081	0.068
MSINPUT							-0.067	0.141	-0.068	0.141
MSOUTPUT							0.071	0.069	0.068	0.069
MSUPPORT									0.565	0.156 ***
CONSTANT	-2.492	0.096 ***	-2.534	0.100	-2.152	0.104 ***	-2.135	0.109 ***	-2.121	0.109 ***
LR test rho=0	1977 ***		1979.7 ***		1660.6 ***		1689.4 ***		1685.7 ***	
Log likelihood	-11074		-11070		-10631		-10557		-10550	
Number of obs	2657		2657		2645		2645		2645	
Wald chi2	1614.8 ***		1621.3 ***		2231 ***		2313.4 ***		2303.1 ***	

Note: (***), (**), (*) means statistically significant at the 1%, 5% and 10% levels respectively

Table 3.13. The determinants of introducing product innovations: Estimation Results for Medium and High Technology Industries 1995-1997 and 1998-2000

	Model1		Model 2		Model 3		Model 4		Model 5	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
MSKILLED	0.701	0.181 ***	0.701	0.181 ***	0.661	0.186 ***	0.673	0.187 ***	0.669	0.187 ***
MLL	0.103	0.026 ***	0.105	0.028 ***	0.094	0.029 ***	0.089	0.029 ***	0.078	0.030 ***
MLRW	-0.120	0.043 ***	-0.120	0.043 ***	-0.254	0.045 ***	-0.235	0.046 ***	-0.233	0.046 ***
LNAGE	0.121	0.031 ***	0.120	0.031 ***	0.150	0.032 ***	0.151	0.032 ***	0.149	0.032 ***
MFOREIGN	0.010	0.001 ***	0.010	0.001 ***	0.010	0.002 ***	0.010	0.002 ***	0.010	0.002 ***
MGROUP	0.121	0.093	0.124	0.094	0.252	0.096 ***	0.277	0.097 ***	0.259	0.098 ***
MRDINT	9.636	2.006 ***	9.606	2.006 ***	9.535	2.029 ***	9.632	2.040 ***	6.770	2.318 ***
MHERF	1.126	0.315 ***	1.154	0.330 ***	1.135	0.338 ***	1.184	0.341 ***	1.223	0.341 ***
MCAPINT	0.139	0.018 ***	0.139	0.018 ***	0.119	0.018 ***	0.129	0.019 ***	0.129	0.019 ***
MMSHARE			-0.134	0.751	-0.364	0.770	-0.419	0.770	-0.795	0.790
MTTRANS					-0.377	0.136 ***	-0.410	0.136 ***	-0.403	0.137 ***
MSECTRD					-3.007	3.384	-2.484	3.422	-3.101	3.437
INTERINT					0.250	0.021 ***	0.239	0.021 ***	0.239	0.021 ***
MLTURN							0.097	0.127	0.111	0.127
MSINPUT							0.201	0.344	0.190	0.344
MSOUTPUT							-2.027	0.359 ***	-2.006	0.358 ***
MSUPPORT									0.349	0.140 ***
CONSTANT	-1.404	0.162 ***	-1.413	0.167 ***	-0.990	0.176 ***	-1.093	0.185 ***	-1.059	0.186 ***

Table 3.14. The determinants of introducing process innovations: Estimation Results for Medium and High Technology Industries 1995-1997 and 1998-2000

	Model1		Model 2		Model 3		Model 4		Model 5	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
MSKILLED	0.631	0.184 ***	0.629	0.184 ***	0.610	0.187 ***	0.558	0.188 ***	0.555	0.188 ***
MLL	0.098	0.026 ***	0.075	0.028 ***	0.071	0.029 **	0.077	0.030 **	0.071	0.030 **
MLRW	-0.164	0.044 ***	-0.167	0.044 ***	-0.264	0.046 ***	-0.265	0.046 ***	-0.264	0.046 ***
LNAGE	0.092	0.032 ***	0.096	0.032 ***	0.121	0.032 ***	0.103	0.033 ***	0.102	0.033 ***
MFOREIGN	0.006	0.001 ***	0.006	0.001 ***	0.005	0.001 ***	0.005	0.001 ***	0.005	0.001 ***
MGROUP	0.531	0.095 ***	0.519	0.095 ***	0.637	0.097 ***	0.669	0.098 ***	0.661	0.098 ***
MRDINT	3.569	1.880 **	3.701	1.883 **	3.496	1.921 *	3.501	1.941 *	2.140	2.188
MHERF	-0.714	0.338 **	-0.965	0.357 ***	-1.136	0.367 ***	-1.261	0.369 ***	-1.241	0.370 ***
MCAPINT	0.175	0.018 ***	0.173	0.019 ***	0.158	0.019 ***	0.166	0.019 ***	0.166	0.019 ***
MMSHARE			1.738	0.769 **	1.943	0.786 ***	1.825	0.787 **	1.634	0.802 **
MTTRANS					-0.404	0.136 ***	-0.434	0.137 ***	-0.431	0.137 ***
MSECTRD					5.506	3.380	6.879	3.417 **	6.583	3.426 *
INTERINT					0.180	0.021 ***	0.181	0.021 ***	0.181	0.021 ***
MLTURN							-0.377	0.127 ***	-0.372	0.127 ***
MSINPUT							0.695	0.338 **	0.691	0.338 **
MSOUTPUT							-1.165	0.280 ***	-1.155	0.280 ***
MSUPPORT									0.177	0.137
CONSTANT	-1.159	0.163 ***	-1.059	0.169 ***	-0.812	0.178 ***	-0.700	0.185 ***	-0.682	0.186 ***
LR test of rho=0:	754.99 ***		756.33 ***		702.25 ***		692.27 ***		690.57 ***	
Log likelihood	-4406.8		-4403.2		-4308.1		-4276.6		-4273.4	
number of obs	1429		1429		1425		1425		1425	
Wald chi(2)	437.14 ***		443.06 ***		595.04 ***		641.44 ***		646.32 ***	

Note: (***), (**), (*) means statistically significant at the 1%, 5% and 10% levels respectively

CHAPTER IV

EMPLOYMENT IMPACT OF PRODUCT AND PROCESS INNOVATIONS

4.1. INTRODUCTION

With the emergence of the industrial revolution, the extensive substitution of labor by machinery incorporating the new technology has led economist and policy makers to debate the economic and social consequences of technological change. The relationship between innovation and employment has long been debated and the vast empirical literature seeks to answer the classical question "*Does technology creates or destroys jobs*?"

The relationship between innovation and employment is a complex one and the empirical studies try to find an answer to the above question by involving new questions to be answered like "what type of innovation are we considering?", "what type of jobs are created or destroyed by innovation?" and "what are the structural, demand and institutional factors which determine the employment effect of innovation?"

This chapter focuses on the effect of product and process innovations on employment in Turkish manufacturing for the periods 1995-1997 and 1998-2000. We hypothesize that these two types of innovations have different impacts on employment. In order to test this hypothesis, we first apply a two stage econometric treatment model to define determinants of the employment growth rate controlling for the endogeneity of introducing product and process innovations. After exploring the determinants of introducing product and process innovations by using several measures of firm and industry specific characteristics, we estimated the employment growth rate by including variables of introducing product and process innovations. We also utilize an additional selection model to evaluate the effects of

product and process innovations that are previously introduced on employment growth rate under the condition that firms did not close down, namely survived until 2000.

The chapter is organized as follows. The next section provides a brief discussion on the theoretical framework regarding the employment effect of technological change and also demonstrates the empirical evidence so far. The third section presents an overview of different types of innovations having different outcomes in terms of employment growth in Turkish manufacturing industries regarding the low and medium and high technology orientation separately. The fourth section demonstrates our empirical models in order to analyze the effects of introducing product and process innovations on the employment growth rate in Turkish manufacturing industries regarding different technology level and summarizes main empirical results from these estimations. The last section gives a brief summary of the findings of this chapter.

4.2. INNOVATION AND EMPLOYMENT GROWTH: THEORETICAL FRAMEWORK

The full view of the employment impact of innovation has to come from a macroeconomic perspective that can consider all the indirect effects through which technological change affects employment. This is usually referred as debate on "*compensation mechanisms*" and a detailed analysis of this debate is in Vivarelli (1995) who evaluates the compensation mechanism theoretically and the way they operate in the economy.

The compensation mechanism *via decrease in prices* is one of the most important ones: new technologies may make lower prices possible, increasing international competitiveness and leading to greater output and to the recovery of the job losses due to the original innovation (Vivarelli, 1995:29). This outcome, however, is conditional on the lack of demand constraints, on the decision of firms to transfer in lower prices the productivity gains due to the innovation, and on the lack of oligopolistic power in the relevant markets (Pianta, 2003:10).

The compensation mechanism *via new machines* based on the argument that the same process technical change that displaces workers, may create new jobs

in the industries where the new means of production are made (Vivarelli, 1995:27). But the rationale for mechanization is by definition saving on the use of labor, putting a limit to the relevance of this mechanism because job losses can also occur within this sector.

The compensation mechanism *via new investment* argues that during the competitive gap between the decrease in costs and the consequent fall in prices, the temporary extra profits available to the innovator may be turned into new investment and hence new productions and new jobs created (Vivarelli, 1995:31). This however may expand production capacity and jobs, or may introduce additional labor saving effects depending on whether earned profits utilized immediately and productively or not and whether investment decisions are devoted to expansionary projects.

The compensation mechanism *via new products* works as new branches arise and new jobs created for the new form of commercialization and of creation of new products. This mechanism is different than other compensation mechanisms that it is not related to market forces stimulated by technological change, but is due to the nature of technological advance itself (Vivarelli, 1995:35). As Vivarelli argues, the compensation mechanism via new products appears to be the most powerful counterbalancing factor of technological unemployment caused by process innovations. However, there may be a displacement of old products if the new ones are substitutes, leading to *substitution effects*.

The compensation mechanism *via decrease in wages* is typical recipe of the neoclassical view of the labor market for solving unemployment entailed by any reason (Vivarelli, 1995:36). As technological unemployment appears, wages would fall and firms would hire more workers leading to also *welfare effects*. This mechanism however is based on strong assumptions on the feasibility of any combination of labor and capital, competitive markets, flexibility of wages and labor markets.

The compensation mechanism *via increase in incomes* operates in the opposite way, through the demand effects of the distribution of part of the gains from innovation to higher wages, as it has happened in large oligopolistic firms in mass production industries (Pianta, 2003:10). However, wage increases can hardly be large enough to sustain additional aggregate demand.

The abovementioned theory established that the relationship between technical change and employment is highly complex and involves direct labor saving effects, compensation forces and alternative forms of technical progress. While this perspective of macroeconomic analysis is the most comprehensive and satisfactory for explaining the overall impact of technological change on employment, the complexity of the construction of the model, the problems in specifying all relevant relationships and the lack of adequate data limit the feasibility of this perspective (Pianta, 2003:11). Alternative to this analysis is to study the effects of technological change and hence innovation (both product and process innovation) on employment at firm and sector level.

The empirical literature analyzing the impact of innovation on employment at the firm and sector level mainly breaks into two main categories. The first one analyzes the impact of technological change on *quality* of employment, leading to a large literature on composition of skills change and wage structures giving emphasis to skill biased technological change[33]. The second category of empirical studies analyze the impact of innovations on *quantity* of employment change, leading to a large literature on the type of innovation (product or process innovations) giving emphasis to structural, demand and institutional factors affecting creation or destruction of jobs.

The studies analyzing the impact on *quality* of employment, report empirical evidence on different country studies comparing the relative composition between skilled and unskilled workers and on wage differences. The issue has generally been investigated using a factor substitution framework, showing that direct and indirect measures of technology like R&D intensity, computer usage and different types of innovation are important in explaining the relative increase in skilled labor (Pianta, 2003:13). The dominant finding of this empirical literature on

[33] Chennells and Van Reenen (1999), Sanders and Weel (2000), Addison and Teixeira (2001) and Brown and Campbell (2002) survey the empirical literature on skill biased technological change emphasizing how technological change has affected wage and employment structures and whether the expansion of international trade is the another cause of increased wage differentials between skilled and unskilled workers that is associated with increased imports of manufacturing goods from less-advanced countries. Acemoğlu (2002) takes another point of view and explores the differences between technological advances of nineteenth-century having replaced skilled workers and expanded tasks performed by unskilled and technological advances of twentieth century being skill biased.

skill bias in industries and firms is that the diffusion of technologies has a strong skill bias effect, while it has a less evident effect on wages.

The firm level studies analyzing the relation between technological change and the change in the decomposition of skilled and unskilled workers using labor demand framework by estimating employment share equations are Bauer and Bender (2004) for Germany covering the periods 1993-1995, Haskel and Heden (1999) for UK covering the periods 1972-1992 using computerization an indirect measure of technological change, Maurin and Thesmar (2004) for French manufacturing firms over the 1984-1995 period and Falk and Seim (2001) for West German service sector firms over the period 1994-1996. On the other hand, firm level studies like, Baldwin and Rafiquzzaman (1999) for Canada over the period 1973-1993, Berman *et al.* (1994) for US manufacturing firms over the period 1979-1989, Piva and Vivarelli (2002) for Italian firms over the period 1991-1997, Dunne *et al.* (1997) for US manufacturing for 1970s and 1980s and Gera *et al.* (2001) for Canadian manufacturing firms over the period 1981-1994 analyze the shift in demand for skilled workers utilizing a translog cost function for the share of skilled and unskilled workers in total wage bill emphasizing the within and between compositional changes in the wage structures.

There are also sector level studies comparing different countries in their changing structures in the composition of skilled and unskilled workers and their shares in total wage bill with giving emphasis to cross country similarities. These are Hollanders and Weel (2002) for six OECD countries from 1975 to 1995 estimating employment share equations for skilled and unskilled workers, Machin and Van Reenen (1998) for US and six other OECD countries from 1973 to 1989 estimating the share of skilled and unskilled workers share in total wage bill, Berman *et al.* (1998) for several countries including US and OECD countries for 1980s and Machin (2001) surveying the changing nature of labor demand giving emphasis to increasing demand for skilled workers, comparing UK and US.

The second category of empirical studies analyzes the impact of innovation on *quantity* of employment by estimating employment equations (total or as growth rate) or analyzing job creation and destruction rates. The evidence on the overall employment impact of innovation at the level of firm tends to be positive; firms which innovate grow faster and are more likely to expand their employment

especially product innovators that non-innovative ones (Pianta, 2003:7). Moreover, the evidence on sector level states that in addition to technological change demand structures have also different impacts on employment.

Firm level studies analyzing the impact of technological change on job creation and destruction rates are Greenan and Guellec (2000) for French manufacturing firms between 1984 and 1991 and Klette and Forre (1998) for Norway over the period 1982-1992. These studies suggest that there is no clear-cut positive relationship between technological change and net job creation giving emphasis to differences in R&D intensities between different technology levels.

One of the studies analyzing the effects of technological change at firm level on employment growth is Blanchflower and Burgess (1998) for UK and Australia for 1990. They estimated three year employment growth rate using dummy variable for introducing new technology, firm size and age, dummy for defining demand structure of the firm, dummy for union status and found that the introduction of new technology is more likely to be associated with employment growth (Blanchflower and Burgess, 1998:130). For Germany, Peters (2004) analyzed the relationship between employment and innovation activities in the period 1998-2000. Following a different methodology, she estimated employment growth rate by utilizing innovation output in terms of sales growth rate generated by new product and process innovations and found that product innovations have a positive impact on the employment growth rate (Peters, 2004:27).

Regarding the empirical studies at firm level measuring the effect of technological change on total employment, these studies estimated reduced employment equations similar to labor demand formulation. Using this method, Van Reenen (1997) analyzed for UK manufacturing firms over the period 1979-1982 including measures of product and process innovation, real wage rate, R&D intensity, dummy for union status, capital and lagged employment and found that technological innovation especially product innovations was associated with higher firm level employment (Van Reenen, 1997:269). In addition, Piva and Vivarelli (2004) for Italian manufacturing firms over the period 1992-1997 found a positive relationship between innovation and employment. Greenhalgh *et al.* (2001) for UK from 1987 to 1994 by estimating a derived demand for total employment depending on targeted output, the price of the factor, the prices of alternative

substitute and complementary factors and measures of technological activity like R&D intensity, found a positive impact of technology on firm-level employment.

The studies at the sector level analyzing the impact of innovation on *quantity* of employment, analyzes both direct employment effects of innovation within firms and indirect effects operating within the industry. These sector level studies evaluates first the competitive redistribution of output and jobs from low to high innovation intensive firms and second the evolution of demand and sectoral value added resulting from the lower prices due to innovation (Pianta, 2003:8). The studies at the sector level state that the sources and opportunities for innovation and job creation are specific in different sectors determining the employment performance. The empirical evidence shows that the employment impact is positive in industries characterized by high demand growth and an orientation towards product innovation, while process innovation leads to job losses (Pianta, 2003:8). For sector level studies, demand factors are important because, an industry's demand is constrained by the composition and dynamics of domestic and foreign demand differently from that of individual firm.

One of the studies at the sector level analyzing the effects of technological change on employment is Antonucci and Pianta (2002) for eight European countries (including Italy, UK, France, Germany and The Netherlands) over the period 1994-1996. They estimated employment growth equations at the sector level giving emphasis to demand conditions and the type of innovation and found that these countries rely on active price competitiveness and introduce process innovations having negative impact on employment that also depends on the evolution of demand (Antonucci and Pianta, 2002:303). Another study Pianta (2001) analyzed the relationship between technological change and employment growth for five European countries (Denmark, Italy, Germany, The Netherlands and Norway) in 1989-1993 with variables accounting for changes in demand, value added, innovation intensity and share of product innovations. He found that product innovations and also changes in demand have a positive impact on employment changes (Pianta, 2001:154).

The above mentioned literature lately started to incorporate organizational innovation measures associated to the introduction of new technologies[34]. Organizational innovation is closely linked to technological change as changes in organizations reflect a variety of business strategies ranging from internal or external growth to restructuring and downsizing. (Pianta, 2003:17). The evidence of an upskilling of some occupations resulting from the complementarities between new ICT technologies and skills suggests that organizational innovation plays a crucial role alongside technological innovation in shaping employment outcomes (Pianta, 2003:16).

The employment outcomes of technological change depends on the way job creation and destruction takes place, wages are set, learning, flexibility and welfare protection are managed and the way compensation mechanisms work. On the other hand, labor market institutions influence the supply of labor, which should match the skill and competence requirements emerging with new technologies (Pianta, 2003:18). The above literature leads to a stylized fact that different measures of technological change and hence different types of innovation have different effects on employment also differentiating with industry structure and demand factors. In other words, it is essential to compare the direct labor-saving effect of process innovations with product innovations having a labor-intensive impact.

The impact of technical change on employment can be analyzed by differentiating depending on the product and process orientation of innovation[35]. Firms that innovate successfully gain an advantage over their competitors in terms of market share or in terms of profits. Whether this advantage results in more or fewer jobs depends upon the type of innovation. A product innovation mainly affecting the demand for product, will have a positive effect on the market share of the firm that innovates and thus on its employment when productivity is held constant (Greenan and Guellec, 2000:549). This positive effect of product innovations on employment level can be limited if there are high substitution effects with other goods provided by the same firm and if new products that

[34] Examples of empirical studies using organizational innovations and their relations with other types of innovation are Bresnahan *et al.* (2002) and Piva *et al.* (2003).

[35] Edquist *et al.* (1998) review extensively the existing literature with the aim of developing framework for assessing the employment effect of different types of innovation.

become process innovations in a later embodiment (Edquist *et al.*, 1998:143). If the new product functionally replaces an old one, either increased or decreased employment may result depending on whether demand for this old replaced product changes.

The effect of process innovation, mainly affecting the cost structure and hence the supply of product, on employment can be analyzed at firm and sector level[36]. At the firm level, on the one hand, the market share of the firm increases thanks to the reduction in price due to higher productivity. On the other hand, the productivity of labor increases generating a reduction in labor demand for a given production level (Greenan and Guellec: 2000:549). Thus, the immediate impact of process innovation depending on the rate of change, the direction of change and the elasticity of substitution between inputs will be labor-saving (Taymaz, 1996:194). At sector level, with the diffusion of new technology, the employment loss in less efficient plants will be partially compensated by growth of new technology using plants in turn depending on the price elasticity of demand, the degree of economies of scale, the monopoly power enjoyed by the innovators and the extent of competition (Taymaz, 1996:194).

As our study will focus on the effects of innovations on employment in Turkish manufacturing industries, lastly we will mention two studies on Turkey. The first study Taymaz (1996), analyzed the impact of technological change but especially process innovations on employment for manufacturing industries at the sectoral level over the period 1985-1992. He first estimated the rate of technological change and later an employment growth equation using the rate of technological change, R&D intensity, real growth rate of sectoral value added, number of product classified in the industry, the average net export ratio, the growth rate of domestic price, average wage rate, average plant size and subcontracted output. He found that technological change has a negative but weak impact on employment growth at sector level (Taymaz, 1996:206).

[36]Reati (1998) discussed the different employment effects of product and process innovations with emphasizing that the analysis of process innovations depend on two conflicting forces: (1) the productivity effect which reduces employment and (2) the compensation effect that is the increase in demand resulting from the increase in the price of the commodity involved which expands employment (Reati, 1998:110). The net effect of process innovations on employment depends on the level of price and income elasticities of demand.

The other study Taymaz (2001) analyzed the effect of product and process innovations on employment growth rate calculated for 1993-1997 period. He tried to determine the employment growth rate by using growth rate in capital stock, employment level for 1993, product and process innovations, subcontracted input and output shares, dummy for technology transfer, average wage rate and the share of skilled and administrative employees. He found that product innovations have a positive impact on employment growth while process innovations have no significant impact (Taymaz, 2001:242).

This study focuses on the effects of product and process innovations on the growth rate of employment. It departs from other studies because we utilize different types of innovations in order to observe the empirically mentioned differences they have on the employment. We utilize a different model to explore the problem of selection bias by applying a two stage econometric treatment model to define determinants of the employment growth rate for firms controlling for the endogeneity of product and process innovations. We also evaluate the long-run effects of product and process innovations on employment growth rate by estimating employment growth rate for firms that did not close down, namely survived.

4.2. INNOVATION AND EMPLOYMENT GROWTH: DESCRIPTIVE ANALYSIS

The vast of argument and evidence indicate that there is a strong positive association between product innovation and employment growth whereas process innovations generally have a net negative effect on employment even though compensation effects exist. In the previous chapter, we evaluated the innovativeness of Turkish manufacturing firms. In what follows, we will explore the structure of employment growth and its relation with product and process innovations. We use the same data used in the previous chapter which covers data on all manufacturing firms employing more than 10 employees and introducing product and/or process innovations over the period 1995-1997 and 1998-2000.

Table 4.1. Employment growth rates, 1995-2000

	1995	1996	1997	1998	1999	2000
Low tech industries						
3-year employment growth rate	0.132	0.041	-0.005	-0.053		
2-year employment growth rate	0.119	0.069	-0.011	-0.016	-0.033	
1-year employment growth rate	0.066	0.053	0.021	-0.029	0.007	-0.036
Medium and high tech industries						
3-year employment growth rate	0.180	0.050	-0.017	-0.096		
2-year employment growth rate	0.157	0.104	-0.032	-0.032	-0.046	
1-year employment growth rate	0.090	0.085	0.021	-0.056	0.015	-0.065

Note: employment growth rates are calculated as mean of firm growth rates
Source: State Institute of Statistics

We calculated three different employment growth rates for 1995-2000 taking into account different technology levels as well (Table 4.1). The first one is the employment growth rate calculated for three years forward. For example, the three year employment growth rate over the period 1995-1998 is 0.132 in low technology industries. The second one is the two year and the last is the one year employment growth rate, respectively. All of the employment growth rates calculated for medium and high technology industries are relatively higher than that of low technology industries when the employment growth rate is positive. Moreover, we observe that the employment growth rates started to decrease gradually becoming negative with the year 1997. This is due to the fact that Turkish manufacturing firms faced with an economic crisis in 1998. For example, one year employment growth rate over the years 1998-1999 was (-0.03) in low technology industries and this rate is relatively lower in medium and high technology industries (-0.06). After a recovery seen in 1999 for one year employment growth rate, manufacturing firms faced the other crisis year of 2000. Furthermore, the decrease in all of the employment growth rates was lower in low technology industries than that of medium and high technology industries. In other words, the employment growth rates in medium and high technology firms were affected from economic crisis severely than that of low technology firms and we observed this as a reduction in employment growth rates.

Table 4.2. Employment growth rates by innovativeness, 1995-1997 and 1998-2000

	1995-1997			1998-2000		
	non innovator	innovator		non innovator	innovator	
Low tech industries						
3-year employment growth rate	0.09	0.23	***	-0.09	0.07	***
2-year employment growth rate	0.09	0.19	***	-0.04	0.10	***
1-year employment growth rate	0.05	0.10	***	-0.04	0.04	***
Medium and high tech industries						
3-year employment growth rate	0.11	0.18	**	-0.15	-0.02	***
2-year employment growth rate	0.11	0.14		-0.05	-0.01	
1-year employment growth rate	0.07	0.08		-0.07	-0.04	*

Note: (*), (**) and (***) means the difference between innovators and non-innovators is statistically significant at 1 %, 5 % and 10 % levels

Source: State Institute of Statistics

Next, we will demonstrate the average employment growth rates for innovators and non innovators over the period 1995-1997 and 1998-2000 for different technology levels (Table 4.2). For low technology industries, the employment growth rates of innovators are significantly higher than that of non innovators. In medium and high technology industries, the employment growth rates of innovators are higher than that of non innovators. But in these industries, the only significant difference between the employment growth rates of innovators and non innovators is attained for three year employment growth rate. Moreover, for the period 1998-2000, the employment growth rates for both low and medium and high technology firms are clearly lower than that for the period 1995-1997. Although, the employment growth rates for non-innovators become negative for both technology levels in this second period, innovators in low technology industries have positive employment growth rates. We can conclude that in low technology industries, being an innovator has a significant positive impact on the employment growth rates.

Table 4.3 demonstrates the average employment growth rates for product innovators and non innovators over the period 1995-1997 and 1998-2000 for different technology levels. For low technology industries, the employment growth rates of product innovators are significantly higher than that of non innovators. In medium and high technology industries, the employment growth rates of product

innovators are also higher than that of non innovators. But in these industries, the only significant difference between the employment growth rates of innovators and non innovators is attained for one year employment growth rate in the first period and three year employment growth rate in the second period. Moreover, for the period 1998-2000, the employment growth rates for both low and medium and high technology firms are clearly lower than that for the period 1995-1997. We can conclude that in low technology industries, being a product innovator has a significant positive impact on the employment growth rates.

Table 4.3. Employment growth rates by product innovativeness, 1995-1997 and 1998-2000

	1995-1997			1998-2000		
	non innovator	innovator		non innovator	innovator	
Low tech industries						
3-year employment growth rate	0.09	0.34	***	-0.07	0.07	***
2-year employment growth rate	0.09	0.27	***	-0.02	0.12	***
1-year employment growth rate	0.05	0.15	***	-0.03	0.03	***
Medium and high tech industries						
3-year employment growth rate	0.13	0.16		-0.13	-0.02	***
2-year employment growth rate	0.12	0.13		-0.04	-0.01	
1-year employment growth rate	0.07	0.10	*	-0.07	-0.04	

Note: (*), (**) and (***) means the difference between innovators and non-innovators is statistically significant at 1 %, 5 % and 10 % levels

Source: State Institute of Statistics

When we look at the employment growth rates for process innovators and non innovators over the period (Table 4.4), the employment growth rates for process innovators are significantly higher than that of non innovators for both technology levels. Moreover, as indicated for product innovators, being a process innovator has a significant positive impact on the employment growth rates for low technology industries.

Table 4.4. Employment growth rates by process innovativeness, 1995-1997 and 1998-2000

	1995-1997			1998-2000		
	non innovator	innovator		non innovator	innovator	
Low tech industries						
3-year employment growth rate	0.11	0.20	***	-0.08	0.08	***
2-year employment growth rate	0.10	0.16	**	-0.03	0.10	***
1-year employment growth rate	0.05	0.09	*	-0.03	0.04	***
Medium and high tech industries						
3-year employment growth rate	0.13	0.18		-0.14	0.01	***
2-year employment growth rate	0.12	0.13		-0.05	0.01	*
1-year employment growth rate	0.07	0.09		-0.06	-0.05	

Note: (*), (**) and (***) means the difference between innovators and non-innovators is statistically significant at 1 %, 5 % and 10 % levels

Source: State Institute of Statistics

By looking at the above tables, we can further compare the average employment growth rates for product and process innovators over the period 1995-1997 and 1998-2000 for different technology levels. The employment growth rates for the period 1995-1997 are positive regardless of the type of innovations and technology level. The employment growth rates for product innovators in low technology industries are higher than that for process innovators over the period 1995-1997. Over the same period, three year employment growth rate for process innovators is still positive and higher than that of product innovators in medium and high technology industries. On the other hand, one year employment growth rate in medium and high technology industries is slightly higher in product innovators.

Furthermore, for the next period (1998-2000), we observe changing patterns in employment growth rates concerning the type of innovations and technology level. In low technology industries, except for the two year employment growth rate, we find out that the employment growth rates of process innovators are higher than that of product innovators and in addition these figures are positive contradictory to the literature. This leads us to conclude that there may be compensation effects such as increased demand resulting from lower production costs or from rising incomes or consumption. In medium and high technology industries, it is interesting to observe that product innovators have negative

employment growth rates. This can be verified that this period covers the crisis year of Turkish economy and there may be demand structure factors such as the price elasticity of demand being less than one, leading to a decline in employment in product innovations. Besides, one year employment growth rate in process innovators is negative in medium and high technology industries for the period 1998-2000.

In below figures, we graph the three year employment growth rates for product and process innovators in low and medium and high technology industries (Figure 4.1-Figure 4.4). The kernel density estimate function plots the frequency of the three employment growth rate and by adding a normal density function we can figure out the frequency plot differences between the two. The three year employment growth rate for process innovators in medium and high technology industries have the closest frequency distribution to normal density function (Figure 4.2). For the other figures, the three year employment growth rate skewed to the right tail of the kernel density function having greater variation around the value 0.

So far, we could not find a clear cut evidence for different impact of introducing product and process innovations on employment growth rate. We just explored that both being product and process innovator have a positive impact on the employment growth rate. In low technology industries being a product or process innovator have a positive significant effect on the employment growth rate especially significant impact observed for product innovators. For the medium and high technology industries, both product and process innovators seem to have positive impact on the employment growth rate.

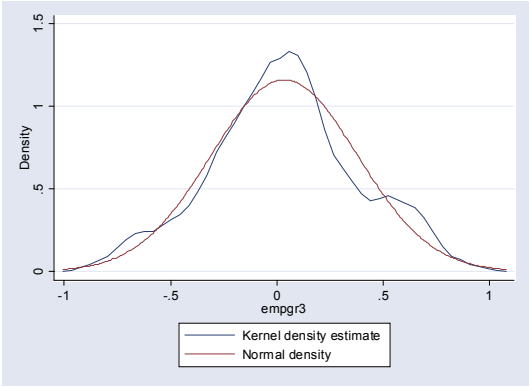

Figure 4.1 Three year employment growth rate for product innovators in medium and high technology industries

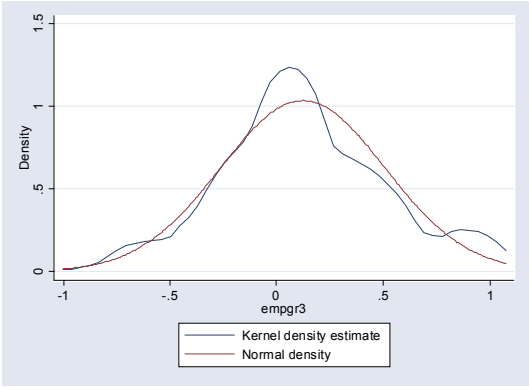

Figure 4.3 Three year employment growth rate for product innovators in low technology industries

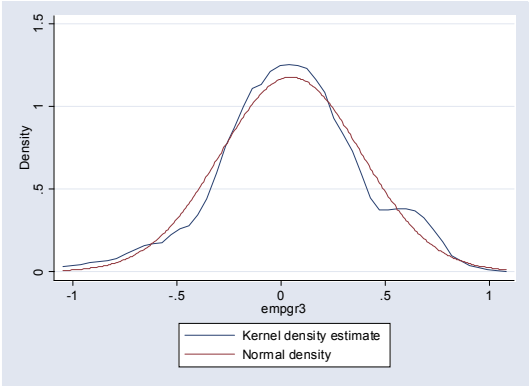

Figure 4.2 Three year employment growth rate for process innovators in medium and high technology industries

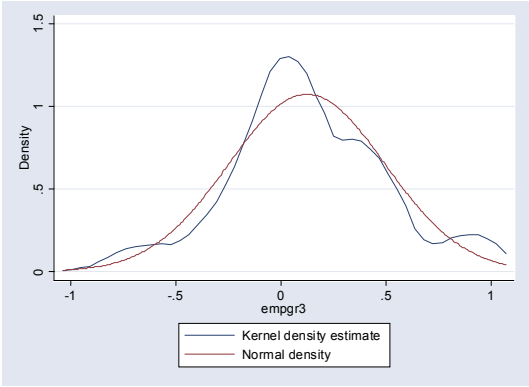

Figure 4.4 Three year employment growth rate for process innovators in low technology industries

Table 4.5. Innovativeness by employment growth rates, 1995-1997 and 1998-2000

	1995-1997		1998-2000	
	product	**process**	**product**	**process**
Low tech industries				
positive 3-year employment growth rate	0.14	0.16	0.17	0.24
Negative 3-year employment growth rate	0.07	0.13	0.11	0.15
positive 2-year employment growth rate	0.14	0.17	0.18	0.24
Negative 2-year employment growth rate	0.07	0.13	0.10	0.14
positive 1-year employment growth rate	0.14	0.18	0.17	0.25
Negative 1-year employment growth rate	0.09	0.13	0.11	0.15
Medium and high tech industries				
positive 3-year employment growth rate	0.32	0.34	0.37	0.33
Negative 3-year employment growth rate	0.20	0.20	0.31	0.25
positive 2-year employment growth rate	0.34	0.29	0.35	0.29
Negative 2-year employment growth rate	0.19	0.30	0.32	0.28
positive 1-year employment growth rate	0.35	0.34	0.35	0.28
Negative 1-year employment growth rate	0.22	0.27	0.33	0.27

Source: State Institute of Statistics

Furthermore, we differentiated the employment growth rates into positive and negative for product and process innovators (Table 4.5). In low technology industries, regardless of the employment growth rates being positive or negative, the share of process innovators is higher than that of product innovators. When we look at the first period in medium and high technology industries, we see that the share of process innovators is higher than that of product innovators if the two and one year employment growth rates are negative. Moreover, the share of product innovators is higher than that of process innovators if the same employment growth rates are positive. However, for the consecutive period, regardless of the employment growth rates being positive or negative, the share of product innovators is higher than that of process innovators. We explore that if the employment growth rates are positive, we have a higher share of process innovators and the opposite holds for product innovators over the period 1995-1997. In other words, in low technology industries, the share of process innovators is higher than that of product innovators regardless of the employment growth rate being positive or negative. In medium and high technology industries, the positive employment growth rates are attained when the share of product innovators is high

and the negative employment growth rates are realized when the share of process innovators is high.

Table 4.6. Sectoral share of product and process innovators by technology level, 1995-1997 and 1998-2000

	1995-1997		1998-2000	
	product	**process**	**product**	**process**
Low tech	0.11	0.16	0.15	0.20
Medium and high tech	0.29	0.29	0.33	0.29

Source: State Institute of Statistics

In order to evaluate the possible spillover effects, we observed the sectoral share of product and process innovators. If the share of product innovators is high in a sector, the incumbent firms may choose to follow a strategy of product innovation in order to compete. In addition, the incumbent firms may also choose to compete on the basis of price competitiveness and decide to introduce process innovations instead. In low technology industries, the sectoral share of process innovators is higher than that of product innovators (Table 4.6). In medium and high technology industries, the share of product and process innovators sectorally are the same in the first period, but in the second period the sectoral share of product innovators are higher than that of process innovators. This fact can be verified by the fact that in low technology industries the share of process innovators is higher than that of product innovators and the opposite finding holds for medium and high technology industries. These product and process innovators create spillovers in the sectors that they exist.

We calculated the number of product and process innovations in sectors in order to clarify possible sectoral factors leading to differences on employment growth impact of different types of innovations (Table 4.7). In low technology industries, the sectoral number of process innovators is higher than that of product innovators regardless of the employment growth rates being positive or negative. For medium and high technology industries, the sectoral number of process

innovators is slightly higher than that of product innovators for two year and one year negative employment growth rates in the period 1995-1997. Moreover, regardless of the direction of the employment growth rates, the sectoral number of product and process innovators is higher in medium and high technology industries than that in low technology industries. Also, the medium and high technology industries have relatively more product innovators at sector level and low technology industries have relatively more process innovators at sector level that is a similar finding in line with the previous chapter.

Table 4.7. Sectoral share of product and process innovators by employment growth rates, 1995-1997 and 1998-2000

	1995-1997		1998-2000	
	product	**process**	**product**	**process**
Low tech industries				
positive 3-year employment growth rate	0.11	0.15	0.15	0.21
Negative 3-year employment growth rate	0.11	0.16	0.14	0.19
positive 2-year employment growth rate	0.11	0.15	0.15	0.20
Negative 2-year employment growth rate	0.11	0.16	0.14	0.19
positive 1-year employment growth rate	0.11	0.15	0.15	0.21
Negative 1-year employment growth rate	0.11	0.16	0.13	0.19
Medium and high tech industries				
positive 3-year employment growth rate	0.29	0.30	0.33	0.28
Negative 3-year employment growth rate	0.27	0.26	0.33	0.29
positive 2-year employment growth rate	0.29	0.28	0.33	0.29
Negative 2-year employment growth rate	0.28	0.31	0.33	0.28
positive 1-year employment growth rate	0.29	0.29	0.34	0.28
Negative 1-year employment growth rate	0.27	0.30	0.33	0.28

Source: State Institute of Statistics

It is clear that the employment growth rates for product and process innovators are positive both in low and medium and high technology industries for Turkish manufacturing firms. We before mentioned that our data consists of two periods that cover the years 1995-1997 and 1998-2000. Having observed the fact that the employment growth rates for product and process innovators are negative both in low and medium and high technology industries for the period 1998-2000,

we further analyze the employment growth rates taking into consideration whether firm survives or not until the end of the period. This will further help us to analyze the effect of crisis period on firms that may lead to possible exit behavior from the industry and contraction in economic performance evaluated here by employment growth rate.

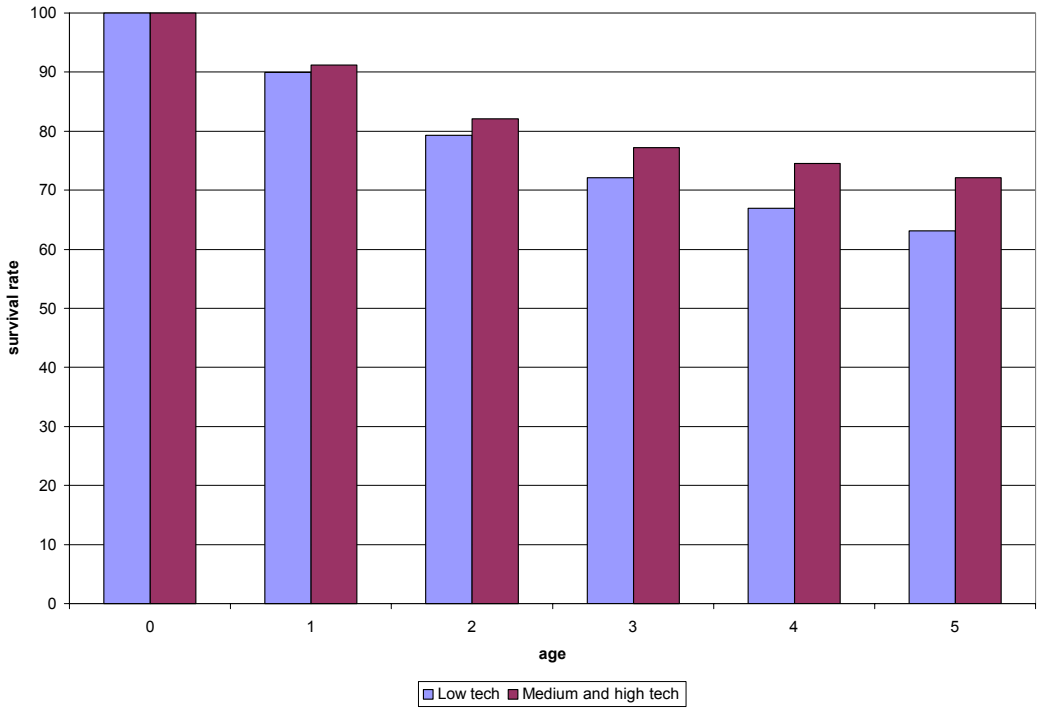

Figure 4.5. Share of surviving firms by technology level, 1995-1999

Source: State Institute of Statistics

We defined a firm as a survivor if the firm still exists in 2000. Figure 4.5 demonstrates the share of surviving firms in low and medium and high technology industries for different time durations. The first two columns display the share of surviving firms in different technology levels for the period 1999-2000. In other words, the share of surviving firms in total number of firms that were operating in 1999 was 90 % in low technology and 91 % in medium and high technology

industries. The share of surviving firms that were also operating in 1995 was 63 % in low technology industries and this share is 72 % for medium and high technology industries. Moreover, the share of surviving firms in medium and high technology industries are higher than that of low technology industries even though for the crisis year of 1998 (labeled as period 4). This can be due to the fact that operating in a higher level of technology provides firm a higher propensity to survive. We further encounter that the share of surviving firms that introduced innovations in 1997 was 87 % regardless of technology level.

Table 4.8. Employment growth rates by survival status of firms, 1995-2000

	1995	1996	1997	1998	1999	2000
Low tech survivor						
3-year employment growth rate	0.164	0.058	-0.009	-0.059		
2-year employment growth rate	0.147	0.095	-0.003	-0.025	-0.033	
1-year employment growth rate	0.086	0.069	0.030	-0.024	0.007	-0.041
Low tech non-survivor						
3-year employment growth rate	-0.026	-0.148				
2-year employment growth rate	0.030	-0.052	-0.176			
1-year employment growth rate	0.032	0.000	-0.061	-0.106		
Medium and high tech survivor						
3-year employment growth rate	0.227	0.063	-0.025	-0.096		
2-year employment growth rate	0.197	0.128	-0.027	-0.034	-0.046	
1-year employment growth rate	0.108	0.099	0.030	-0.042	0.015	-0.063
Medium and high tech non-survivor						
3-year employment growth rate	0.029	-0.154				
2-year employment growth rate	0.085	-0.037	-0.183			
1-year employment growth rate	0.059	0.021	-0.064	-0.130		

Note: We label a firm as survivor if it still exists in 2000 and as non-survivor otherwise
Source: State Institute of Statistics

Table 4.8 demonstrates the different employment growth rates for survivor and non-survivor firms in low and medium and high technology industries. The employment growth rates for survivor firms in low technology industries are higher than that of non-survivor firms. This outcome is an expected one because the firms may exit as they face with lower rates of employment growth. The employment

growth rates for survivor firms in medium and high technology industries are also higher than that of non-survivor firms. The other point to be mentioned about the employment growth rates is that regardless of the surviving status, the employment growth rates again are higher in medium and high technology industries than that of low technology ones. We again face with the negative effects of crisis year that is associated with a decrease in the employment growth rates.

The employment growth rates of a firm that survived and also introduced product innovations may be different than that of the one introducing process innovations (Table 4.9). In low technology industries, survivor firms introducing product innovations has positive and higher employment growth rates than that of firms introducing process innovations in the period 1995-1997. For this period, the difference between the employment growth rates for product and process innovators is also significant. For the second period, we can only observe one year employment growth rate due to our survival status definition. The employment growth rate for both product and process innovators turns out to be negative but this time, it is higher for process innovators in this second period. In other words, if low technology process innovator firms have the chance to survive until 2000, they have a higher employment growth rate than that of product innovators.

Table 4.9. Employment growth rates for survivor firms by innovativeness, 1995-1997 and 1998-2000

	1995-1997		1998-2000	
	product	**process**	**product**	**process**
Low tech industries				
3-year employment growth rate	0.075 ***	0.065 ***		
2-year employment growth rate	0.041 **	0.057 ***		
1-year employment growth rate	0.084 ***	0.044 *	-0.061	-0.026
Medium and high tech industries				
3-year employment growth rate	-0.061	-0.056		
2-year employment growth rate	-0.030	-0.068		
1-year employment growth rate	0.043	-0.005	-0.010	0.012

Note: (*), (**) and (***) means the difference between innovators and non-innovators is statistically significant at 1 %, 5 % and 10 % levels

Source: State Institute of Statistics

In medium and high technology industries, survivor firms introducing both product and process innovations have negative employment growth rates except for one year employment growth rate. For one year employment growth rate, we observe that survivor firms introducing product innovations have a positive employment growth rate in the period 1995-1997 which is also higher than that of process innovators. However, this situation is reversed when we observe the second period. So, for medium and high technology process innovator and survivor firms have a higher employment growth rate than that of product innovators.

Table 4.10. Innovativeness by survival status, 1995-1997 and 1998-2000

	1995-1997		1998-2000	
	product	**process**	**product**	**process**
Low tech industries				
Survivor	0.13	0.20	0.15	0.20
non-survivor	0.05	0.03		
Medium and high tech industries				
Survivor	0.32	0.28	0.33	0.28
non-survivor	0.19	0.29		

Source: State Institute of Statistics

We further evaluate the share of process and product innovators in survivor and non-survivor firms by technology level (Table 4.10). The share of process innovators in survivor firms is higher than that of product innovators in low technology industries. However, the share of product innovators in non-survivor firms is slightly higher than that of process innovators. So, in low technology industries survivor firms have a higher probability to be process innovators and non survivor firms have a higher probability to be product innovators. In medium and high technology industries, the share of product innovators is higher than that of process innovators for survivor firms. In contrast to survivor firms, the share of process innovators is higher than that of product innovators in non-survivor firms that is opposite to the case in low technology industries. This clarifies the different

strategy of product and process innovators in search for technological competitiveness and price competitiveness in different technology levels.

Table 4.11. Sectoral share of product and process innovators by survival status, 1995-1997 and 1998-2000

	1995-1997		1998-2000
	survivor	**non-survivor**	**survivor**
Low tech industries			
share of product innovators	0.11	0.11	0.15
share of process innovators	0.16	0.15	0.20
Medium and high tech industries			
share of product innovators	0.29	0.28	0.33
share of process innovators	0.27	0.31	0.28

Source: State Institute of Statistics

When we look at the sectoral share of product and process innovators for survivor and non-survivor firms (Table 4.11), we observe that there is no difference between survivor and non-survivor firms in their sectoral share of product and process innovators in low technology industries. However, in medium and high technology industries, the sectoral share of process innovators is higher in non-survivor firms than that of survivor firms. Another point to mention is that both in low and medium and high technology industries, both the sectoral number of product and process innovators increase if firms survive until period 1998-2000. But, the sectoral share of process innovators is lower in the firms that survived until 2000 compared to the ones that did not survive.

To sum up, *different than empirical evidence that product innovations having positive and process innovations having negative employment impact, we find that the employment growth rate for both product and process innovators is positive in Turkish manufacturing industries*. Regardless of technology level and type of innovation, both introducing product and process innovations have a positive significant effect on the employment growth rate and this impact is especially significant in low technology industries.

As we confront the fact that the employment growth rates for product and process innovators are negative both in low and medium and high technology industries for the period 1998-2000, we further analyze the employment growth rates taking into consideration whether firm survives or not until the end of the period. We find out that the employment growth rates for survivor firms are higher than that of non-survivor firms. These survivor firms are dominantly product innovators in medium and high technology industries and are process innovators in low technology industries. In brief, the strategy focusing on product innovation follows from a search for technological competitiveness, based on high productivity and higher probability to survive in medium and high technology industries. On the other hand, the strategy focusing on process innovations follows from a search to survive with cost savings and price competitiveness in low technology industries.

In low technology industries, survivor firms introducing product and process innovations have positive employment growth rates in the period 1995-1997. In addition, the employment growth rates for product innovators are higher than that of firms introducing process innovations in the period 1995-1997. We before found out that the share of process innovators was higher than that of product innovators in low technology industries. If low technology process innovator firms have the chance to survive until 2000, they have a higher employment growth rate that that of product innovators in the second period. For medium and high technology industries, survivor firms introducing both product and process innovations have negative employment growth rates except for one year employment growth rate. The three year employment growth rate is higher if these survivor firms are also process innovators. Moreover, those medium and high technology process innovator and survivor firms have a higher employment growth rate than that of product innovators in the period 1998-2000. Concisely, low technology survivor and process innovators have a negative but higher employment growth rates in 1998-2000 and the medium and high technology counterparts of these firms have a positive and still higher employment growth rates than that of product innovators in 1998-2000.

4.4. EMPLOYMENT IMPACT OF PRODUCT AND PROCESS INNOVATIONS: ECONOMETRIC ANALYSIS

4.4.1. EMPLOYMENT IMPACT OF INNOVATIONS

In order to evaluate the impact of product and process innovations on employment growth rate, we will utilize a two stage treatment effect model similar to that we have used in the first chapter. We will evaluate the impact of introducing innovations in 1995-1997 and 1998-2000 on the three year employment growth rate calculated for these periods under the condition that the firms have introduced product and /or process innovations. We first applied bivariate probit model in order to find out the determinants of introducing product and process innovations using the same method and models estimated in previous chapter. By this way, we take into account that the decision to innovate that has impact on employment growth rate is actually endogenous and determined by other factors. Later, in the second stage of treatment effect model, we estimated the three year employment growth rate with the correction term estimated in the first stage bivariate probit model that is the selection rule for firms introducing innovations and also with our endogenous variables of being product or process innovator.

The fist stage bivariate probit model that explores the determinants of introducing product and process innovations is the last general model used in the previous chapter and is defined as :

$$\begin{aligned}
&(PRODUCT, PROCESS)_{i,t} = \alpha_0 + \alpha_S (SKILLED)_{i,t} + \alpha_L \ln(L)_{i,t} \\
&+\alpha_W \ln(RW)_{i,t} + \alpha_A \ln(AGE)_{i,t} + \alpha_F (FOREIGN)_{i,t} + \alpha_G (GROUP)_{i,t} \\
&+\alpha_{RD} (RDINT)_{i,t} + \alpha_H (HERF)_{i,t} + \alpha_C (CAPINT)_{i,t} + \alpha_{MS} (MSHARE)_{i,t} \\
&+\alpha_T (TTRANS)_{i,t} + \alpha_{SRD} (SECTRD)_{i,t} + \alpha_I (INTERINT)_{i,t} + \alpha_{LT} (LTURN)_{i,t} \\
&+\alpha_{SO} (SOUTPUT)_{i,t} + \alpha_{SI} (SINPUT)_{i,t} + \alpha_{SR} (SUPPORT)_{i,t} + \varepsilon_{i,t}
\end{aligned} \tag{4.1}$$

where the subscripts i and t denote the firms ($i = 1,...,n$) and time $t = 1995-1997, 1998-2000$, respectively. The dependent variable is dummy variable taking the value 1 if firm introduces a product and/or process innovation (*PRODUCT, PROCESS*) and taking the value zero otherwise. *SKILLED* is the share of skilled personnel in total employment of firms, L is the number of

employees (measured in logarithmic form) , *RW* is the average real wage rate deflated by input price index, *AGE* is the age of firms (measured in logarithmic form) , *FOREIGN* is a dummy variable taking the value 1 if the firm has a foreign ownership, *GROUP* is a dummy variable taking the value 1 if the firm belongs to an industrial group, *RDINT* is the R&D intensity of firms, *HERF* is the Herfindahl index that is measured as the summation of the square of each firm's market share showing the concentration rate, *CAPINT* is the capital intensity of firms measured by depreciation over total employment, *MSHARE* is the market share of firms measured as the ratio of firm output to total sectoral output, *SECTRD* is the sectoral R&D intensity of firms capturing the R&D spillovers from other firms, *TTRANS* is the technology transfer, *INTERINT* is the internet usage intensity, *LTURN* is the labor turnover as the measure of labor market flexibility, *SINPUT* and *SOUTPUT* are the share of subcontracted inputs and outputs respectively and finally, *SUPPORT* is dummy variable taking value 1 if firm received R&D support.

Our baseline model in the second stage of treatment effect modeling in order test the impact of product and process innovations on employment consists of only variables concerning innovation level factors and is as follows:

$$\begin{aligned} EMPGR_{i,t} &= \beta_0 + \beta_{PR}(PRODUCT)_{i,t} + \beta_{PS}(PROCESS)_{i,t} \\ &+ \beta_{SPR}(SPRODUCT)_{i,t} + \beta_{SPS}(SPROCESS)_{i,t} + \beta_L \ln(L)_{i,t} \\ &+ \beta_A \ln(AGE)_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4.2}$$

where the subscripts *i* and *t* denote the firms ($i = 1,...,n$) and time *t= 1995, 1998*, respectively. The dependent variable *EMPGR* is the three year employment growth rate calculated between 1995-1997 and 1998-2000 in logarithmic form. *PRODUCT* is a dummy variable taking the value 1 if firm introduces product innovations, *PROCESS* is a dummy variable taking the value 1 if firm introduces process innovations, *SPRODUCT* is the sectoral share of product innovators in total number of firms, *SPROCESS* is the sectoral share of process innovators, *L* is the number of employees (measured in logarithmic form) and *AGE* is the firm age (measured in logarithmic form).

The possible effects of product and process innovations on employment growth rate are discussed in the literature survey section. We expect to have a

positive impact of product innovation on employment growth rate but this impact may change concerning the elasticity of demand. We expect to have a negative impact of process innovation on employment growth rate but this impact may also change due to effectiveness of compensation mechanisms. We included the sectoral share of product and process innovators into our employment growth model. As the sectoral share of product innovators increase, we expect the employment growth rate to be positively affected. The same may hold for the sectoral share of process innovators if they have positive impact on employment growth with compensation mechanism dominated. But if the process innovations have a negative impact on employment, the increase in the sectoral share of process innovators will have a negative impact on the employment growth rate. The firm specific size and age is utilized to check for size and age effects on employment growth rate that are expected to have positive coefficients.

We later included the interaction term for size and age of product and process innovators into our employment growth model. *LPRODUCT* is an interaction term for the size of product innovators calculated by multiplying the dummy variable for introducing product innovations with the size of firm, *LPROCESS* is the size of process innovators, *APRODUCT* is an interaction term for the age of product innovators calculated by multiplying the dummy variable for introducing product innovations with the age of the firm and finally *APROCESS* is the age of process innovators. As the size and age of product or process innovator increases, we expect the impact of product and process innovations to change.

We also included a group of variables in order to check the effects of technological opportunity on the employment growth rate. *TTRANS* is a dummy variable taking the value 1 if firms transfer technology. If firms transfer technology in order to increase their capability to conduct R&D activities and to introduce innovations and hence to increase their performance, like employment growth, we expect technology transfer to be positively related to employment growth. The share of skilled employees (*SKILLED*) is another variable added in order to check technological capability of firms.

We further included the average wage rate (*LRW*) and the growth rate of capital stock (*CAPINTGR*) into our model. The average wage rate in logarithmic form is utilized to observe the labor cost effects on the employment growth rate. If

there are wage differentials between sectors, employment growth will be lower in high wage industries (Taymaz, 1996:205). The growth rate of capital stock calculated by the same method as in employment growth rate calculation and is utilized to check for the effect of changes in capital stock on employment growth which is found to be positive in Taymaz (2001). This variable also will help us to evaluate possible substitution or complementary effect between capital and labor.

Lastly, we included sector level variables like concentration ratio measured by Herfindahl index (*HERF*) and the sectoral growth rate of output (*SECTGR*). The growth rate of sectoral output measured as value added at sector level and calculated over three years, should have a positive impact on employment growth because the demand for labor will increase in expanding sectors. Regarding the concentration ratio, we want to test the impact of market structure on employment growth due to possible different effects this variable may have on the decision to introduce produces and product innovations.

Table 4.12. Summary statistics

Variable	definition	mean	std. dev.	min	max
PRODUCT	dummy for product innovation	0.30	0.46	0	1
PROCESS	dummy for process innovation	0.32	0.47	0	1
SPRODUCT	sectoral share of product innovators	0.20	0.16	-1.38	0.83
SPROCESS	sectoral share of process innovators	0.22	0.13	-1.38	0.79
LPRODUCT	size of product innovator	1.50	2.43	0	9.01
LPROCESS	size of process innovator	1.67	2.52	0	8.81
AGEPRODUCT	age of product innovator	0.84	1.35	0	4.57
AGEPROCESS	age of process innovator	0.92	1.40	0	4.61
LL	number of employees (log)	4.66	1.26	2.30	9.22
LNAGE	age (log)	2.71	0.79	0	4.61
TTRANS	dummy for technology transfer	0.05	0.21	0	1
SKILLED	share of skilled employees	0.18	0.14	0	1
LRW	average real wage rate (log)	4.64	0.80	1.42	7.07
LTURN	labor turnover rate	0.25	0.23	0	1.00
LRP	real labor productivity (log)	5.73	1.06	-2.45	11.69
CAPINT	capital intensity	3.05	1.57	-5.30	10.48
DEBT	debt ratio	0.03	0.23	0	34.73
HERF	concentration ratio	0.06	0.07	0	0.99
CAPINTGR	growth rate of capital stock	0.02	1.37	-7.71	7.81
SECTGR	growth rate of sectoral output	0.11	0.63	-6.18	4.22

Table 4.12 demonstrates summary statistics for the variables used in the empirical models and Table 4.13 displays the impact of product and process innovations on three year employment growth rate for the years 1995 and 1998 in low technology industries. The first model (Model 1) incorporates dummy variables for introducing product and process innovations, firm size, age of firm and sectoral share of product and process innovators as explanatory variables. The product innovations do not have a significant impact on the employment growth rate of Turkish low technology manufacturing firms. On the other hand process innovations, contrary to the findings of the literature and Taymaz (2001) have a positive impact on the employment growth rate at the 1% significance level. This outcome can be verified by the outweighing impact of compensation mechanisms in process innovations. In other words, the compensation effects such as increased demand resulting from lower production costs or from rising incomes and consumption that are outcomes of productivity enhancing process innovations, are large enough to make net employment effect of process innovations positive (Edquist *et al.*, 1998:137).

The sectoral number of product innovators has a negative impact on the employment growth rate in low technology industries. As the sectoral number of product innovators increase, the employment growth rate in low technology industries decreases due to labor saving effects of newly introduced product innovation. Moreover, as firms get larger and older, they decrease their employment. In other words, smaller and young firms have a more favorable development of employment than their larger and older counterparts in spite of their higher probability of having financial and technological resource problems. Besides, this verifies their flexible and dynamic structure and the arguments about their better economic performance.

In Model 2, we included the interaction terms which are the age and size of product and process innovators, to check for the magnitude of the impact of introducing product and process innovations that can vary with the age and size. In this model, introducing product innovations have negative and introducing process innovations have positive impact on the employment growth rate. The sectoral number of product innovators, the age and size of firm decreases the employment growth rate as in the previous model. When we explore the impact of size of

product and process innovators, we see that the size of product and process innovations have positive impact on the employment growth rate. However, the age of process innovators have negative impact on the employment growth rate.

In order to decide exact relationship between introducing product and process innovations and the employment growth rate, we have to take into account the interaction terms as well. The actual impact of introducing product innovations that is the coefficient of the dummy variable for being product innovator plus the average firm size in low technology industries multiplied by the age of the product innovators plus the average firm age in these industries multiplied by the age of the product innovators, is equal to -0.204 [-0.411 + (0.052 * 3.78) + (0.004 *2.68)] and this impact is higher in larger product innovator firms that have scale advantages spreading this product innovation into whole production process and leading to labor saving. The actual impact of introducing process innovations that is calculated utilizing the interaction terms, is equal to 0.691 [0.713 + (0.050 * 3.78) + (-0.079 * 2.68)] and this impact is higher in large and young process innovators in low technology industries. In other words, the employment growth rate increases as process innovators in low technology industries become larger and younger. Moreover, the employment growth rate decreases in low technology industries as product innovators become larger.

Model 3 includes the variables determining the technological capability of firms. As the share of skilled employees and the rate of technology transfer increases, the employment growth rate in low technology industries decreases. This may be due to the fact that the external knowledge embodied in technology transfer has labor saving nature in low technology industries. All other variables have the same sign and significance levels as they used to have in the previous model. The impact of introducing product innovations is negative and equal to (-0.10) and this negative impact of product innovations on the employment growth rate of low technology industries increases as firms get older and larger. The impact of introducing process innovations is positive and equal to 0.57 and this positive impact increases as firms are relatively larger and younger.

In order to test for labor costs effects and the effect of capital stock growth rate may have on employment growth rate, we also included the average wage rate and growth rate of capital stock in Model 3. As the labor costs increase, the

employment growth rate decreases in low technology industries. For the capital stock growth rate, contradictory to the positive coefficient outcome of Taymaz (2001), we found a negative relationship at 1 % significance level between the growth rate of capital stock and employment. This suggests that capital and labor in low technology industries are substitutes.

Going one step further, we incorporated industry specific characteristic like the concentration rate and sectoral growth rate of output into our model (Model 4). The employment growth rate is lower if firms operate in concentrated markets. The sectoral output growth rate has positive coefficient. In low technology industries, as firms operate in expanding sectors, they also increase their demand for labor. All other variables have the same signs and significance levels. The impact of introducing product innovations on the employment growth rate of low technology industries is negative and the opposite holds for introducing process innovations.

Second part of Table 4.13 demonstrates the impact of product and process innovations on three year employment growth rate in medium and high technology industries. As firms introduce product innovations, their employment growth rate contracts wheras, the employment growth rate increases with introducing process innovations (Model 1). As the share of product innovators increase in the sector, the employment growth rate diminishes. This leads us to conclude that medium and high technology firms are affected negatively from spillovers created by product innovators in the sector and they decrease their demand for labor. Unlike the results attained in low technology industries, as the sectoral share of process innovators increase, the employment growth rate increases in medium and high technology industries indicating positive interaction between firms. We have similar coefficients concerning the firm size and age that are attained for low technology industries. As firm size and age increases, the employment growth rate slows down and this outcome is also valid for low technology industries. In other words, small and young firms in Turkish manufacturing industry seem to generate higher employment regardless of technology level.

Model 2 includes the interaction terms to control for age and size effects of product and process innovators on the employment growth rate in medium and high technology industries. Unlike the case in low technology industries, adding the interaction term between age and being innovator makes the coefficient of firm

age insignificant. The employment growth rate in medium and high technology industries increases with the size of product and process innovator firms. In low technology industries, the age of process innovators has a significant impact on the employment growth rate but in medium and high technology industries, the age of product innovators has a significant impact on the employment growth rate. Introducing product innovations have a negative (-0.30) and significant impact on the employment growth rate and this impact is higher in relatively larger and younger product innovator firms. The employment growth rate increases with introducing process innovations and this positive impact (0.77) strengthens as firms get larger in size.

When we look at technological opportunity variables added in Model 3, we identify transferring technology and employing higher share of skilled employees do not have any impact on the growth rate of employment in medium and high technology industries. The labor costs on the other hand have a positive impact on the employment growth rate. As the growth rate of capital stock increases, the employment growth rate decreases that is a possible outcome of substitution effect. There is no change in the signs and significance levels of other variables when we added these new variables into previous model.

When we examine the effects of concentration rate on the employment growth rate (Model 4), we see that as firms operate in concentrated markets, they have an increasing employment growth rate. However, the employment growth rate in low technology industries used to decrease with the concentration rate. When we look at the sectoral output growth rate, we see that the output growth rate at the sector level also has a positive impact on the employment growth rate of medium and high technology industries. The impact of introducing product and process innovators on the employment growth are still negative and positive, respectively.

To sum up, *the impact of introducing process innovations on the employment growth rate is positive and the impact of introducing product innovations is negative regardless of the technology level*. Another similar finding regardless of technology level is that as firms become larger, their employment growth rate decreases. Moreover, the employment growth rate decreases with the age of the firm in low technology industries but firm age does not have any impact on the employment growth rate of medium and high technology industries.

The growth rate of capital stock has a negative impact on the employment growth rate regardless of the technology level. This finding may suggest that labor and capital are substitutes in Turkish manufacturing industries. Moreover, as the sectoral output growth rate increases, the employment growth rate also increases regardless of the technology level. Regardless of technology level, the size of product and process innovators strengthens the impact of both introducing product and process innovations. In low technology industries, the impact of introducing process innovations is higher as the age of innovator decreases but in medium and high technology industries, the impact of introducing product innovations is higher as the age of innovator decreases. This is not a contradictory finding because the share of process innovators is higher in low technology industries and while the share of product innovators is higher in medium and high technology industries.

Table 4.13. Employment impact of product and process innovations in low and medium and high technology industries: Estimation Results

	Low tech industries								*Medium and high tech industries*							
	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 1**		**Model 2**		**Model 3**		**Model 4**	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
PRODUCT	-0.083	0.058	-0.411	0.083 ***	-0.299	0.083 ***	-0.236	0.083 ***	-0.362	0.076 ***	-0.492	0.107 ***	-0.474	0.108 ***	-0.398	0.111 ***
PROCESS	0.651	0.062 ***	0.713	0.085 ***	0.599	0.085 ***	0.562	0.085 ***	0.874	0.084 ***	0.400	0.124 ***	0.325	0.123 ***	0.376	0.127 ***
SPRODUCT	-0.237	0.047 ***	-0.226	0.047 ***	-0.216	0.047 ***	-0.197	0.047 ***	-0.170	0.049 ***	-0.139	0.048 ***	-0.158	0.048 ***	-0.179	0.048 ***
SPROCESS	-0.040	0.043	-0.022	0.043	-0.038	0.042	-0.015	0.042	0.255	0.061 ***	0.246	0.059 ***	0.248	0.059 ***	0.250	0.058 **
LL	-0.087	0.004 ***	-0.108	0.004 ***	-0.098	0.005 ***	-0.101	0.005 ***	-0.076	0.008 ***	-0.152	0.009 ***	-0.151	0.010 ***	-0.156	0.010 ***
LNAGE	-0.088	0.006 ***	-0.074	0.006 ***	-0.064	0.006 ***	-0.062	0.006 ***	-0.064	0.010 ***	-0.006	0.012	-0.010	0.012	-0.001	0.012
LPRODUCT			0.052	0.011 ***	0.044	0.011 ***	0.046	0.011 ***			0.153	0.015 ***	0.147	0.015 ***	0.139	0.015 ***
LPROCESS			0.050	0.010 ***	0.050	0.010 ***	0.049	0.010 ***			0.063	0.016 ***	0.067	0.016 ***	0.062	0.015 ***
APRODUCT			0.004	0.017	0.012	0.017	0.009	0.017			-0.141	0.025 ***	-0.134	0.024 ***	-0.147	0.024 ***
APROCESS			-0.079	0.014 ***	-0.070	0.014 ***	-0.066	0.014 ***			0.005	0.025	-0.003	0.025	-0.001	0.025
TTRANS					-0.105	0.041 ***	-0.114	0.041 ***					-0.028	0.033	-0.023	0.032
SKILLED					-0.052	0.026 **	-0.044	0.026 *					0.069	0.047	0.021	0.046
LRW					-0.032	0.007 ***	-0.028	0.007 ***					0.020	0.011 *	0.025	0.011 **
CAPINTGR					-0.045	0.003 ***	-0.044	0.003 ***					-0.036	0.005 ***	-0.039	0.005 ***
HERF							-0.592	0.092 ***							0.218	0.104 **
SECTGR							0.042	0.008 ***							0.076	0.007 ***
Constant	0.515	0.019 ***	0.559	0.021 ***	0.645	0.028 ***	0.643	0.028 ***	0.296	0.037 ***	0.445	0.040 ***	0.383	0.050 ***	0.339	0.049 ***
number of obs	2415		2415		2415		2415		1275		1275		1275		1275	
F-test	25.31 ***		18.98 ***		17.73 ***		16.48 ***		15.34 ***		18.89 ***		15.87 ***		16.83 ***	
Log likelihood	-1467		-1453		-1425		-1418		-581.7		-533.3		-519.4		-497.9	

Note: (*), (**), (***) means statistically significant at the 1 %, 5 % and 10 % levels

4.4.2. LONG-RUN EMPLOYMENT IMPACT OF INNOVATIONS

In order to evaluate the long-run impact of product and process innovations on employment growth rate, we will utilize a selection model similar to that we have used in the previous modeling. Moreover, the selection model we utilized is different than treatment effects model because this time we do not have an endogenous variable included into our second stage estimation model. We will explore the impact of introducing innovations in period 1995-1997, the first survey period, on the employment growth rate for the period 1998-2000. Moreover, we will estimate this employment growth model under the condition that firms did not close down in 2000 using Heckman's selection model[37]. This method is used by Brouwer *et al.* (1993) to analyze the influence of innovation on growth rates of employment for Dutch manufacturing firms over the period 1983-1988. They first estimated a probit model identifying factors influencing the probability that a firm will not close down by using firm size, industry dummies and sales growth at firm level. Using this information as a correction term in OLS model, they tried to explain the effect of R&D intensity as a technology measure on the employment growth rate (Brouwer *et al.*, 1993:158).

Our first stage model in this selection modeling explores the factors that affect the probability of firm to survive and is defined as:

$$
\begin{aligned}
&(SURVIVAL)_{i,t} = \theta_0 + \theta_L \ln(L)_{i,t} + \theta_T (LTURN)_{i,t} + \theta_W \ln(RW)_{i,t} \\
&+\theta_P \ln(RP)_{i,t} + \theta_C (CAPINT)_{i,t} + \theta_A \ln(AGE)_{i,t} + \theta_D (DEBT)_{i,t} + \theta_H (HERF)_{i,t} \\
&+\varepsilon_{i,t}
\end{aligned}
\tag{4.3}
$$

where the subscripts *i* and *t* denote the firms ($i = 1,...,n$) and time $t = 1997 - 2000$, respectively. The dependent variable *SURVIVAL* is a dummy variable taking the value 1 if firm survives until 2000 or zero otherwise. *L* is the number of employees in logarithmic form indicating the size of the firm, *LTURN* is the labor turnover measured as the ratio of the sum of the number of employees who left the firm in a year and who were hired by the firm in that year to the average number of

[37] For a further discussion about Heckman selection method, see Heckman (1979)

employees (average employment plus the number of employees who were hired and fired by the firm in a year), *RW* is the average wage rate in logarithmic form, *RP* is the labor productivity in logarithmic form calculated as the value added per employee, *CAPINT* is the capital intensity in logarithmic form calculated as the value of depreciation per employee, *AGE* is the firm age measured in logarithmic form, *DEBT* is the financial obligation of the firm calculated as the ratio of interest payments in total output and *HERF* is the concentration ratio for the industry.

Firm size and age are the most important variables determining the firm dynamics and hence survival of firms found in empirical studies (Audretsch *et al.*, 2000:5). Large firms are more likely to survive as they have financial and scale advantages. The firm age has a positive impact on the probability to survive since new start-up firms carry a higher risk to exit. As Evans (1987) found, the probability of survival generally increases with the age and the size of the firm.

Labor turnover indicating labor market flexibility is one of the determinants affecting firm survival because as labor turnover increases, the probability to survive will be lower. The average wage rate reflects the demand for industry specific skills. In high wage industries, firms will face difficulties in hiring the workers they need. The average wage rate is incorporated in the model to test if paying higher wages decreases the probability to survive (Taymaz, 1997:109).The level of labor productivity is found to be relatively high in industries where investment requirements are indivisible and massive. The probability to survive will increase with higher values of labor productivity (Wagner, 1999:262).

The capital intensity of firm is an important determinant of firm survival since firms should be able to offset any capital disadvantage through their own capital intensity. As firms have higher capital intensity, their probability to survive will increase where the scale economies play an important role enabling firms to take cost advantages (Audretsch *et al.*, 2000:5). Furthermore, if capital investments have a substantial sunk cost component, the more capital intensive firms should exhibit more persistence (Tveteras and Eide, 2000:70). The debt structure of a firm is hypothesized to have a negative influence on the probability of survival because having a high debt ratio will limit the cash flows available to firm (Audrestch *et al.*, 2000:7). The effect of concentration ratio is found to be positive in the probability

of survival. If the firm is operating in a concentrated industry, it may be protected from competition and hence more likely to survive.

The probability of making a product or process innovation affects a firm's decision to remain in or exit from an industry, because innovative activity is a vehicle by which a firm can grow (Audrestch, 1991:444). We included *PRODUCT* that is a dummy variable taking the value 1 if firm introduces product innovations, *PROCESS* that is a dummy variable taking the value 1 if firm introduces process innovations to control for the effects of innovative activity on the probability of survival. Those firms that introduce product and process innovations can expect future sales growth while those that do not introduce product and process innovations but have only prospects of innovating are more likely to exit from the industry. Moreover, the probability to survive may change depending on the strategy followed by firm in deciding to introduce product or process innovations. As aforementioned, the strategy to introduce product innovations incorporates higher level of technological capability. These technologically advanced firms may have a higher chance to survive. However, Wagner (1999) found that being a product innovator is no way to insure against exit. He found that for German manufacturing industries, the share of exits among firms that introduced at least one product innovation is nearly double the share among the non-innovator firms (Wagner, 1999:259).

Moreover, we incorporated the sectoral share of product (*SPRODUCT*) and process innovators (*SPROCESS*) into our survival model. As the sectoral share of product and process innovators increase, this may lead firms to exhibit exit from the industry as they have to compete with a high number of innovators. As it is found that the probability of firm survival increases with firm size, we included interaction terms between product and process innovators and size. An increase in the size of product (*LPRODUCT*) and process innovators (*LRPOCESS*) may strengthen the effect of being product and process innovators on the likelihood of survival.

Using the above described model to analyze the determinants of the probability of firms' survival in 2000, we first estimate the probability of survival in 2000 and display these result. Then utilizing one of these survival models as a selection process, we estimated the same employment growth rate model used in

the previous section to explore the impact of being product and process innovator in the period 1995-1997 on the employment growth rate over the next period under the condition that firms did survive using Heckman selection model.

Table 4.14 displays the determinants of survival in low and medium and high technology industries. The first model includes firm size and age, labor turnover, labor productivity, the average wage rate, capital intensity, the debt structure and the concentration rate for the industry as explanatory variables. For low technology industries, the probability of survival increases with firm size but contradictory to the literature the probability of survival decreases with firm age. Larger and less mature firms have a higher to survive in low technology industries. The probability of survival is not affected from labor turnover, labor productivity and also from the average wage rate of firms. The capital intensity increases the probability to survive in low technology industries and this verifies the importance of having capital advantages in these industries. The probability of survival decreases as low technology firms have a higher share of debt in their total sales. Moreover, concentration does not have any significant impact on the survival probability of low technology firms.

The second model incorporates the dummy variables indicating the product and process innovator firms. Being a product innovator decreases the probability of survival and being a process innovator increases the probability of survival in low technology industries. This can be verified only with Wagner (1999) finding that product innovators still have the risk to exit the industry. All other variables have the same sign and significance levels like they have in the previous model.

The last model includes the sectoral share of product and process innovators and the interaction term between the size and dummy indicating product and process innovators. The sectoral share of product and process innovators both have negative but insignificant impact on the probability of survival. As the size of product innovators increase, the probability of survival increases for low technology firms. The actual survival probability of product innovators that is the average firm size multiplied by the coefficient of the age of product innovator and subtracted from the coefficient of being a product innovator itself, is equal to -0.57 and still negative. As the size of process innovators increase, the probability of survival decreases for low technology firms. With the same calculation, the actual

effect of being process innovator on the survival probability of low technology firms is equal to 1.63 and positive. All other variables have the same sign and significance levels as before.

For medium and high technology industries, Model 1 demonstrates that the survival probability increases with firm size and in addition the firm age also has a positive impact on the survival probability of medium and high technology firms opposite to low technology firms. In other words, large and mature firms in medium and high technology industries have a higher chance to survive. The capital intensity and the share of debt in total sales have the same impacts on the probability of medium and high technology firm survival that of low technology firms. Contradictory to what we observed in low technology industries, the probability of survival increases with labor turnover and labor productivity in medium and high technology industries. Moreover, relatively higher average wage rate paid decreases the probability of survival in these industries. The concentration of the industry does not have significant impact on the survival probability.

Model 2 which includes dummy variables of being product and process innovators indicates that being a product innovator increases the probability of firm survival in medium and high technology industries but being a process innovator decreases this probability. This can be verified that medium and high technology firms compete by introducing product innovations and hence using technological competitiveness strategy. So, being a process innovator in these industries does not eliminate the probability of exit decision. This outcome is also opposite to the case attained for low technology industries where firms usually choose to follow price competition strategy and hence decide to introduce process innovations.

The last model that incorporates the sectoral share of product and process innovators into survival modeling specifies that as the sectoral share of product and process innovators increase, the probability of survival for medium and high technology firms decreases. So, there are negative spillover effects deterring the innovative activity of other firms. The size of product innovators decreases the probability of survival in medium and high technology firms. The actual impact of being product innovator on the survival probability of firms is equal to 0.25 and positive. Although the size of process innovators does not have a significant impact on the survival probability of medium and high technology firms, the actual impact

of being process innovator is nearly equal to 3.80 offsetting the negative impact of being process innovator on the survival probability. All other variables have the same sign and significance level except labor productivity and the firm age. The labor productivity does not affect the survival probability and in addition the significance level of firm age increases in this last model.

Using the last model (Model 3) that incorporates both the firm and industry level variables and also variables explaining the innovative activity of firms, we estimated three year employment growth rate of firms that survived until 2000 by Heckman's selection method. We did not display the estimation results of survival model as it does not change with different modeling of employment growth rate.

Table 4.14. The determinants of survival in low and medium and high technology industries: Estimation Results

	Low tech industries						*Medium and high tech industries*					
	Model 1		**Model 2**		**Model 3**		**Model 1**		**Model 2**		**Model 3**	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
LL	0.328	0.024 ***	0.324	0.024 ***	0.381	0.026 ***	0.600	0.066 ***	0.554	0.066 ***	0.418	0.077 ***
LTURN	0.008	0.090	0.071	0.091	0.048	0.092	0.899	0.230 ***	0.765	0.232 ***	0.554	0.242 **
LRW	-0.007	0.046	0.036	0.047	0.064	0.047	-0.504	0.103 ***	-0.499	0.104 ***	-0.481	0.108 ***
LRP	0.031	0.026	-0.004	0.028	-0.023	0.029	0.163	0.056 ***	0.140	0.057 ***	0.056	0.060
CAPINT	0.150	0.017 ***	0.120	0.017 ***	0.122	0.018 ***	0.087	0.033 ***	0.106	0.033 ***	0.144	0.035 ***
LNAGE	-0.045	0.023 **	-0.081	0.024 ***	-0.082	0.025 ***	0.117	0.062 *	0.153	0.063 **	0.175	0.065 ***
DEBT	-2.369	0.280 ***	-2.441	0.283 ***	-2.457	0.281 ***	-0.565	0.223 **	-0.566	0.227 ***	-0.623	0.223 ***
HERF	0.503	0.502	0.444	0.513	0.755	0.530	-0.757	0.696	-0.725	0.695	-0.637	0.752
PRODUCT			-0.404	0.091 ***	-1.401	0.449 ***			0.293	0.126 **	1.877	0.449 ***
PROCESS			1.137	0.100 ***	4.676	0.486 ***			-0.554	0.110 ***	-3.860	0.482 ***
SPRODUCT					-0.209	0.291					-1.109	0.396 ***
SPROCESS					-0.270	0.278					-1.087	0.490 **
LPRODUCT					0.217	0.095 **					-0.435	0.116 ***
LPROCESS					-0.805	0.097 ***					1.007	0.142 ***
CONSTANT	-0.616	0.175 ***	-0.514	0.175 ***	-0.683	0.181 ***	-0.498	0.349	-0.251	0.358	1.123	0.460 **
number of obs	6340		6340		6340		1507		1507		1507	
LR chi2	487.97 ***		665.14 ***		769.74 ***		241.62 ***		266.96 ***		343.15 ***	
Log likelihood	-2575.61		-2487.03		-2434.72		-579.35		-566.69		-528.59	

Note: (*), (**), (***) means statistically significant at the 1 %, 5 % and 10 % levels

Table 4.15 demonstrates the three year employment growth rates for low and medium and high technology industries under the condition that firms survived in 2000. The first model includes only dummy variables for being product and process innovators, the sectoral share of product and process innovators, the firm size and age. In low technology industries, being a product innovator has a significant positive impact and being a process innovator has a positive but insignificant impact on the employment growth rate. As the sectoral share of product innovators increase, the employment growth rate decreases due to negative spillover effects from other firms in the sector. Large and mature firms have a contracting employment growth rate in low technology industries indicating that small and young firms are relatively more dynamic and have a higher employment generation rate.

Model 2 incorporates the interaction terms that are the age and size of product and process innovators into Model 1. As the size of product innovator increases, the employment growth rate for these firms becomes negative. The size of process innovators has a positive impact on employment growth rate. Although the age of product innovators does not have a significant impact on the employment growth rate, the age of process innovators has a negative employment effect. The actual impact of being product innovator, that is the coefficient of product plus the average size of firms multiplied by the size of product innovator plus the average age of firms multiplied by the age of product innovators, is equal to 0.17 [0.410 +(-0.081 *3.78) + (0.028 * 2.68)] and still positive. In other words, the impact of product innovators on employment is positive and also this impact is higher in small and older product innovator firms. When we calculated the actual impact of being process innovator, we see that this value is equal to (– 0.016) and negative although the coefficient of being process innovator is insignificant. In other words, the impact of process innovators on employment is negative and also this impact is higher in large and young process innovator firms in low technology industries.

We included technology transfer and the share of skilled employees in the next model to see the effect of technological capability on the employment growth rate of low technology firms (Model 3). Technology transfer doe not have significant impact on employment growth rate but the share of skilled employees

has a negative impact on the employment growth rate. This model also incorporates the average wage rate and three year growth rate for capital stock. Although, the average wage rate has no significant impact, the growth rate of capital stock has a negative impact on the employment growth rate. This indicates that capital and labor are substitutes in low technology industries. All other variables have the same sign and significance levels as in the previous model. The impact of being product innovator on employment growth rate is equal to 0.19 and this impact is higher in small and young product innovators as before. Although the coefficient of being process innovator is not significant, the impact of being process innovator on the employment growth rate is negative (-0.018) and this impact is higher in large and young process innovator firms as before.

The last model (Model 4) is the general including sector level variables like concentration rate and the three year sectoral output growth rate. The employment growth rate is not affected from the market structure of industry. However, as the sectoral output growth rate increases, the employment growth rate in low technology industries also increases due to expanding output. The impact of being product innovator has a significant and positive impact on the employment growth rate of low technology firms. Although the coefficient of being process innovators is not significant, the impact of being process innovators on the employment growth rate is negative.

For medium and high technology industries, Model 1 indicates that both being product and process innovator have positive but insignificant effect on the employment growth rate. As the sectoral share of product innovators increase, the employment growth rate decreases in medium and high technology industries that is a similar finding to the one in low technology industries indicating negative spillover effects from other firms. As firms get older, they have a slower employment growth rate like the ones in low technology industries. However, firm age is positively associated with the employment growth rate in medium and high technology industries. In other words, as firms get older in medium and high technology industries, they have a higher employment growth rate.

Model 2 which includes the interaction terms for age and size of product and process innovators demonstrates that being a product innovator has a negative impact on the employment growth rate in medium and high technology industries.

The sectoral share of product innovators and the firm size still have negative impact on the employment growth rate. However, the firm age has a positive but insignificant impact on the employment growth rate when we included the interaction terms. Both the size of product innovators and the age of process innovators have positive impact on the employment growth rate that are opposite to the case attained for low technology firms. The actual impact of being product innovator on the employment growth rate of medium and high technology firms is equal to (-0.125) and this negative impact is higher in large product innovator firms. Although the coefficient of being process innovator is not statistically significant, the impact of being process innovator on the employment growth rate is positive (0.016) and this impact is higher in mature process innovators.

Model 3 incorporates technology transfer, share of skilled employees, the average wage rate and the growth rate of capital stock additional to the explanatory variables existing in Model 2. The share of skilled employees has a positive impact on the employment growth rate of medium and high technology industries. As these firms actually employ higher share of skilled employees, this hare is expected to have a positive impact on the employment growth rate. The employment growth rate in medium and high technology industries increases with the average wage rate. This is contradictory to our expectations, since the employment growth rate will decrease in firms facing higher labor costs. The growth rate of capital stock has no significant impact on the employment growth rate of medium and high technology industries. Moreover, the coefficient of the size of process innovators becomes significant and it has a negative impact on the employment growth rate. The impact of being process innovator on the employment growth rate is positive (0.02) and this impact is higher in smaller and older process innovator firms. The impact of being product innovator on the employment growth rate of medium and high technology firms is negative (-0.01) and this impact is higher in large and older product innovator firms.

For the last model, the only significant variable that is newly added is the sectoral growth rate of output and the employment growth rate increases as the sectoral output expands in medium and high technology industries. The effect of being product and process innovator is both negative but insignificant that is a different finding than that of other models. The impact of being product innovator

on the employment growth rate of medium and high technology firms is (-0.007) and this impact is higher in large and older product innovator firms. On the other hand, the impact of being process innovator on the employment growth rate is positive (0.02) and this impact is higher in small and older process innovator firms.

4.5. CONCLUSION

Employment impacts of innovations depend on the type of innovation, the demand structure and industry specific characteristics. In this chapter, we focus on the effect of product and process innovations on employment in Turkish manufacturing industries for the periods 1995-1997 and 1998-2000.

Our descriptive analyses demonstrate that the employment growth rates for product and process innovators are positive both in low and medium and high technology industries. In order to test the effect of product and process innovations on employment, we first apply a two stage econometric treatment model to define determinants of the employment growth rate controlling for the endogeneity of introducing product and process innovations. After exploring the determinants of introducing product and process innovations, we estimated the employment growth rate by controlling for product and process innovations. We find that the impact of process innovations on employment growth rate is positive and the impact of product innovations on employment growth rate is negative regardless of the sectoral technological level.

This finding contradicts the earlier empirical literature where the impact of process innovations on employment is found to be negative and the impact of product innovations on employment is found to be positive. The only logical explanation to this outcome may rest on the offsetting compensation mechanism operating in the case of process innovations. The fact that product innovations affect mainly the demand for the product leads to an increase in the demand for labor at the sectoral level. However, employment at the economy level depends on interactions among all sectors and the interaction between supply and demand conditions. Moreover, a new product may require less labor input as a result of improvements in product design. In such a case, the demand for labor may even decrease at both firm and sectoral level.

Having observed the fact that the employment growth rates for product and process innovators are negative both in low and medium and high technology industries for the period 1998-2000 in descriptive analysis, we further analyze the employment growth rate by utilizing selection model to evaluate the long-run effects of product and process innovations on employment growth rate under the condition that firms did not close down, namely survived until 2000.

We first model the determinants of survival and find that the probability of survival increases with firm size and capital intensity and decreases with firm age in low technology industries. However, the survival probability in medium and high technology industries increases with firm size, firm age, labor productivity and capital intensity. Being a product innovator decreases the probability of survival and being a process innovator increases the probability of survival in low technology industries. Unlike low technology industries, being a product innovator increases the probability of survival and being a process innovator decrease the probability of survival in medium and high technology industries. The explanation for this outcome is the difference in the innovative activity strategy followed by firms having different technology orientations. In low technology industries, the only possible way to survive may depend on active price competitiveness that is usually achieved by process innovations in these industries. Whereas, the strategy to survive applied by firms operating in medium and high technology industries rests on technological competitiveness that is extensively achieved by product innovations.

When we evaluate the estimation results on surviving firms, the impact of product innovations on employment in low technology industries is positive and also this impact is higher in small and older product innovator firms. The impact of process innovations on employment is negative and also this impact is higher in large and young process innovator firms in low technology industries. In medium and high technology industries, the impact of being product innovator on the employment growth rate is negative and higher in large product innovator firms. Although the coefficient of being process innovator is not statistically significant, the impact of being process innovator on the employment growth rate is positive and this impact is higher in mature process innovators operating in medium and high technology industries.

Table 4.15. The impact of product and process innovations on the employment growth rate of survivor firms in low and medium and high technology industries: Estimation Results

	Low tech industries								*Medium and high tech industries*							
	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 1**		**Model 2**		**Model 3**		**Model 4**	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
PRODUCT	0.132	0.023 ***	0.410	0.115 ***	0.421	0.116 ***	0.408	0.116 ***	0.025	0.033	-0.279	0.168 *	-0.318	0.168 **	-0.261	0.168
PROCESS	0.022	0.019	-0.016	0.106	-0.005	0.107	-0.016	0.107	0.026	0.032	-0.100	0.167	-0.010	0.170	-0.049	0.169
SPRODUCT	-0.462	0.092 ***	-0.546	0.092 ***	-0.539	0.091 ***	-0.567	0.092 ***	-0.401	0.093 ***	-0.370	0.095 ***	-0.364	0.095 ***	-0.353	0.095 ***
SPROCESS	-0.020	0.089	0.055	0.089	0.052	0.089	0.057	0.089	0.053	0.111	0.027	0.112	0.029	0.114	0.076	0.116
LL	-0.089	0.006 ***	-0.095	0.007 ***	-0.099	0.007 ***	-0.099	0.007 ***	-0.086	0.012 ***	-0.100	0.016 ***	-0.117	0.017 ***	-0.114	0.018 ***
LNAGE	-0.047	0.008 ***	-0.020	0.009 **	-0.018	0.009 **	-0.022	0.009 **	0.035	0.017 **	0.012	0.019	-0.002	0.020	-0.001	0.020
LPRODUCT			-0.081	0.019 ***	-0.086	0.019 ***	-0.089	0.019 ***			0.078	0.029 ***	0.069	0.029 **	0.064	0.029 **
LPROCESS			0.078	0.017 ***	0.080	0.017 ***	0.082	0.017 ***			-0.044	0.028	-0.050	0.028 *	-0.050	0.028 *
APRODUCT			0.028	0.031	0.037	0.031	0.046	0.031			-0.005	0.047	0.018	0.047	0.005	0.047
APROCESS			-0.110	0.023 ***	-0.118	0.023 ***	-0.116	0.023 ***			0.102	0.046 **	0.079	0.046 *	0.094	0.046 **
TTRANS					0.084	0.068	0.080	0.068					0.106	0.068	0.111	0.068
SKILLED					-0.185	0.040 ***	-0.186	0.040 ***					0.181	0.074 ***	0.211	0.074 ***
LRW					0.005	0.012	0.003	0.012					0.059	0.022 ***	0.060	0.023 ***
CAPINTGR					-0.019	0.005 ***	-0.019	0.005 ***					-0.011	0.010	-0.008	0.010
HERF							0.154	0.151							-0.082	0.182
SECTGR							0.042	0.016 ***							0.052	0.016 ***
CONSTANT	0.564	0.031 ***	0.519	0.035 ***	0.533	0.053 ***	0.550	0.054 ***	0.336	0.071 ***	0.452	0.080 ***	0.241	0.104 **	0.199	0.108 *
Number of obs	1196		1196		1194		1194		600		600		599		599	
Wald chi2	350.7 ***		415.6 ***		467.67 ***		476.29 ***		78.13 ***		93.99 ***		113.02 ***		124.51 ***	
Log likelihood	-5278		-5246		-5219		-5215		-1060		-1052		-1034		-1028	

Note: (*), (**), (***) means statistically significant at the 1 %, 5 % and 10 % levels

CHAPTER V

CONCLUSION AND DISCUSSION

This thesis assesses how technology policy, R&D activities and innovativeness interact to yield higher economic performance. We first evaluate the impact of R&D support programs on the demand for researchers in Turkey over the period 1993-2001. The descriptive analysis indicates that the number of manufacturing firms conducting R&D constitutes on the average 70 % of total number of all R&D conducting firms in Turkey and 28 % of these R&D conducting firms received R&D support from TTGV and/or TİDEB. These support receiving firms operate dominantly in medium technology industries and they were relatively more R&D intensive both at firm and sector level. When we examine the share of researchers in total R&D personnel by support status, we see that R&D support-receiving firms employ more researchers than firms that do not receive R&D support but there is no strong evidence that these support receiving firms pay higher wages to researchers than firms that do not receive R&D support.

We hypothesize that receiving R&D support encourages firms to demand more researchers to intensify their R&D activities and test this hypothesis by estimating a two stage treatment effect model that solves the problem of selection bias. This selection model treats the receipt of R&D support as endogenous and accounts the different propensities of firms to be publicly funded to find out the effects of R&D supports on demand for researchers.

The estimation results concerning the determinants of receiving R&D support in Turkish manufacturing firms demonstrate that size, previous R&D intensity, share of skilled employees, sectoral R&D intensity, spillovers and previous support receiving status increase the probability of receiving R&D support. Regarding the demand for researchers, receiving R&D support encourages firms to demand more researchers.

In the third chapter, we analyze the determinants of introducing product and process innovations in Turkish manufacturing industries over the period 1995-1997 and 1998-2000. The descriptive analysis regarding the characteristics of product and process innovators in Turkish manufacturing industries indicates that the proportion of innovative firms is 23 % for 1995-1998 and 30 % for 1998-2000 and these firms dominantly operate in medium and high technology industries. In low technology industries, the share of process innovators is higher than that of product innovators and the opposite is maintained for product innovators that have a higher proportion in medium and high technology industries. Moreover, we observe that the proportion of process innovators is higher than that of product innovators in SMEs and as firms become larger, the share of both product and process innovators decrease.

In line with the outcomes of descriptive analysis indicating that the existing differences between product and process innovators mostly stemmed from technological orientation of the industry, we evaluate the determinants of introducing product and process innovations by estimating a bivariate probit model including both product and process innovations simultaneously.

The estimation results demonstrate that the determinants of introducing product and process innovations are related but they vary with the technological orientation and opportunity of the industry. The positive effect of firm age, firm size, being R&D and capital intensive and negative effect of the average wage rate does not change with the type of innovation and technology level. In Turkish manufacturing industries, large and older firms utilize their advantages of economies of scale and financing opportunities regardless of the type of innovation and technology level. Moreover, the probability of introducing product innovations is higher in concentrated markets.

Technology transfer has a positive impact on the probability of introducing innovations in low technology industries while, it has a negative impact on the probability of introducing innovations in medium and high technology industries. This indicates that technology transfer is an important source of knowledge especially in low technology industries and that medium and high technology industries evaluates a higher value to internal knowledge sources. Moreover, R&D spillovers from other firms are relatively more important for low technology firms

than that of medium and high technology ones. The proportion of employees who have direct access to the internet on the job, namely internet usage intensity have a positive impact on the probability of introducing both product and process innovations regardless of the technology level, leading us to conclude that the internet access is regarded as one of the basis of information by Turkish manufacturing firms.

In the fourth chapter, we analyze the effect of product and process innovations on employment in Turkish manufacturing industries over the periods 1995-1997 and 1998-2000. The descriptive analyses demonstrate the impact of both product and process innovations on the employment growth rate are positive in Turkish manufacturing industries regardless of technology level.

In order to analyze the impact of innovations on the employment growth rate, we estimate two different econometric models. We first apply a treatment effect model controlling for the endogeneity of innovations and find that the impact of process innovations on the employment growth rate is positive and the impact of product innovations is negative regardless of the technology level. Moreover, the impact of product and process innovations on the employment growth rate strengthens as firms become larger regardless of the sectoral technological level.

This finding contradicts the earlier empirical literature where the impact of process innovations on employment is found to be negative and the impact of product innovations on employment is found to be positive. The only logical explanation to this outcome may rest on the offsetting compensation mechanism operating in the case of process innovations in Turkey. The fact that product innovations affect mainly the demand for the product leads to an increase in the demand for labor at the sectoral level. However, employment at the economy level depends on interactions among all sectors and the interaction between supply and demand conditions. Moreover, introducing a new product in Turkey seems to require less labor input as a result of improvements in product design and the demand for labor decreases at both firm and sectoral level in this specific case.

Having observed the fact that the employment growth rates for product and process innovators were negative both in low and medium and high technology industries for the period 1998-2000 in descriptive analysis, we further analyze the employment growth rate by utilizing selection model to evaluate the long-run

effects of product and process innovations on employment growth rate under the condition that firms did not close down, namely survived until 2000.

We first model the determinants of survival and find that the probability of survival increases with firm size and capital intensity in both technological orientations. Moreover, the firms are more likely to survive if they are younger in low technology industries and if they are older in medium and high technology industries. Being a product innovator decreases the probability of survival and being a process innovator increases the probability of survival in low technology industries. Unlike low technology industries, being a product innovator increases the probability of survival and being a process innovator decreases the probability of survival in medium and high technology industries.

The possible reason behind this outcome is the difference in the innovative activity strategy followed by firms having different technology orientations in Turkey. In low technology industries, the only possible way to survive may depend on active price competitiveness that is usually achieved by process innovations in these industries. Whereas, the strategy to survive applied by firms operating in medium and high technology industries rests on technological competitiveness that is extensively achieved by product innovations.

When we evaluate the estimation results on employment growth rate of surviving firms, the impact of product innovations on employment in low technology industries is positive and also this impact is higher in small and older product innovator firms. On the other hand, in medium and high technology industries, the impact of being product innovator on the employment growth rate turns out to be negative and higher in large product innovator firms. However, the impact of process innovations on employment growth rate is negative but insignificant regardless of technology level.

This thesis dwells on unfolding three distinct phases in the process of technological change. The first distinct phase is the creation of new idea that has the potential to be applied in the economy. The analysis regarding the evaluation of the effects of R&D support on R&D activities through its impact on demand for researchers provides insights into this first phase. The second phase is the first commercial application of invention that is innovation. We explore this second phase by analyzing the determinants of generating product and process innovations

through investigating technological and economic conditions in which the innovator operates. This analysis sheds light on the necessity of evaluating the third phase, imitation, that is referred as the diffusion of the innovation to other firms and sectors. This last phase of technological change is assessed in this thesis- because the economic impact of an innovation is observed in this phase in which the technology is now used in many places- by evaluating the employment impact of innovations.

Despite the fact that R&D support receiving firms remain at quite poor levels compared to developed countries, R&D support receiving is conducive to conducting R&D activities. R&D support programs play a crucial role in the maintenance of R&D activities in Turkish manufacturing industry. As our findings strongly suggest, benefits from R&D support are likely to be attained in the form of increased demand for researchers. Moreover, R&D support programs have also shifted the attention of firms toward technological activities that operated in the same sector as importance of sectoral share of support receiving and sectoral R&D intensity verified the existence of positive sectoral spillovers. Another point to mention is that R&D conducting and also R&D support receiving firms are more likely to be larger although we controlled for selection bias. The possible policy proposition in line with this finding is to encourage small firms to apply for these support programs by informing them extensively about these programs.

Regarding the innovativeness of Turkish manufacturing industries, we observe that the orientation of low technology firms is towards generating process innovations and the orientation of medium and high technology firms is towards generating product innovations. We also observe the benefits of R&D support receiving to be reaped in the form of increased innovativeness especially in medium and high technology product innovator firms. Findings concerning the role of firm size and age emphasize the already distinguishable movement of empirical scholars testing the Schumpeterian hypotheses. Although technological opportunity and technological capability of firms are themselves subject to change, these conditions are important in determining inter-industry differences in innovative activity. So, movement from a narrow concern with the role of firm size and market concentration toward a broader consideration incorporating other measures

of opportunity, appropriability and demand structures may provide guidance in identifying the sources of industry level differences.

The finding that innovators having higher employment growth rate especially in low technology industries shows that innovativeness relatively identify the economic performance more in these industries. The negative impact of product innovations on employment growth and positive impact of process innovations on employment growth regardless of technology is different than the ongoing empirical finding. However, we explain this by the fact that controlling for endogeneity of innovations indicates different mechanism like compensation effect other than simple employment effect.

The evidence shows that it is essential to discriminate between product innovation and process innovation having different employment impacts. Moreover, aggregate demand and macroeconomic conditions are important because they play a key role in creating the conditions for a positive impact of innovations on employment. The employment impact of innovations also depends on the way compensation mechanisms work.

The impact of product innovations on the employment growth rate is positive in low technology industries if firms still exist in the industry in 2000. In contrast, being a product innovator in medium and high technology industries has a negative impact on the employment growth rate if firms are able to survive. This is an interesting outcome indicating that product innovations in medium and high technology industries may not lead to economic success especially in a crisis period. For industries, with low technological opportunity, being a product innovator increases the employment growth rate instead.

The employment growth rates attained by innovators in low technology industries are higher than that in medium and high technology industries. Moreover, the positive impact of product innovations on employment in low technology industries is strengthened with long-run employment impact of product innovations. These findings are vital in proposing policy recommendations concerning the employment.

Three key principles for policy action emerge from above evidence. The first is the need for providing R&D supports intended to encourage conducting R&D activities extensively. The second is the need for targeting industries with

greater potential for growth and employment, and for specific actions directed at the needs of individual industries. The third is the need for a strong coherence between industrial, technology, learning and macroeconomic policies. These policy actions are important not only to affect the rate and direction of R&D activities but also to enhance innovativeness and sustained economic growth.

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APPENDIX A

CLASSIFICATION OF MANUFACTURING INDUSTRIES

Code	Industries	Level
311	Food manufacturing	Low Tech
312	Food manufacturing	Low Tech
313	Beverage industries	Low Tech
314	Tobacco manufactures	Low Tech
321	Manufacture of textiles	Low Tech
322	Manufacture of wearing apparel, except footwear	Low Tech
323	Manufacture of leather and products of leather, leather substitutes and fur, except footwear and wearing apparel	Low Tech
324	Manufacture of footwear, except volcanized or moduled rubber or plastic footwear	Low Tech
331	Manufacture of wood and wood and cork products, except furniture	Low Tech
332	Manufacture of furniture and fixtures	Low Tech
341	Manufacture of paper and paper products	Low Tech
342	Printing, publishing and allied industries	Low Tech
351	Manufacture of industrial chemicals	Medium Tech
352	Manufacture of other chemical products	Medium Tech
3522	Manufacture of drugs and medicine	High Tech
353	Petroleum refineries	Low Tech
354	Manufacture of miscellaneous products of petroleum and coal	Low Tech
355	Manufacture of rubber products	Medium Tech
356	Manufacture of plastic products not elsewhere classified	Medium Tech
361	Manufacture of pottery, china and earthenware	Low Tech
362	Manufacture of glass and glass products	Low Tech
369	Manufacture of other non-metallic mineral products	Low Tech
371	Iron and steel basic industries	Low Tech
372	Non-ferrous metal basic industries	Medium Tech
381	Manufacture of fabricated metal products except machinery and equipment	Low Tech
382	Manufacture of machinery exc. electrical	Medium Tech
3825	Manufacture of office and computing machinery	High Tech
383	Manufacture of electrical machinery apparatus, appliances and supplies	High Tech
3832	Manufacture of radio, TV and communication equipment	High Tech
384	Manufacture of transport equipments	Medium Tech
3845	Manufacture of aerospace	High Tech
385	Manufacture of professional and scientific, and measuring and controlling equipment not elsewhere classified, and of photographic and optical goods	High Tech
390	Other manufacturing industries	Medium Tech

Source: OECD (1992)

APPENDIX B

TURKISH SUMMARY

AR-GE DESTEĞİ, YENİLİK VE İSTİHDAM OLUŞUMU: TÜRKİYE DENEYİMİ

Teknolojinin, ekonominin gelişmesindeki rolünü anlayabilmenin anahtarı teknolojik bilginin yaratılması, kullanılması ve edinilmesi ile piyasa süreçleri arasındaki etkileşimi firmanın varolan bilgisi ile birleştirmektedir. Bilginin üretilmesi ve yaygınlaştırılması ile ilgili ekonomik özellikler- kamusal mal niteliğinin önemli olması, belirsizlik, bölünememe, dışsallıklar- birbirleriyle etkileşerek teknolojik yeniliklerin üretilmesinde piyasaların aksayabileceğini ve bu faaliyetlere toplumsal olarak etkin düzeyde kaynak tahsis edilemeyeceğini göstermiştir. Bilginin üretilmesindeki belirsizlikler ve yeniliğin sonuçlarının eşit/simetrik dağılmaması devletin müdahalesi için gerekçe oluştururken, bu müdahalenin teknolojik yenilik faaliyetlerinde özel getiri oranını toplumsal getiri oranına eşitleyecek şekilde teknolojik yenilik faaliyetlerine finansal destek sağlanmasına yönelik bir politika uygulaması olmasının önemini vurgulamaktadır.

Teknoloji politikalarını meşrulaştıran temel etken, piyasaların aksaması sonucu bu faaliyetlere yeterli kaynak ayrılmamasıdır. Bu gerekçe, özel AR-GE faaliyetlerinin devlet desteği ile teşvik edilmesinin AR-GE için ayrılan kaynakların etkin bir şekilde tahsis edilmesindeki önemini vurgulamaktadır. Devletin firmaların kendi kaynakları ile kamunun finansal katkılarını birleştirebildiği en önemli politika araçlarından biri AR-GE destekleridir. AR-GE destek programlarının gelişmiş ülkelerde teknolojik gelişimin yaratılması ve yaygınlaştırılması için önemli bir politika aracı haline gelmesi ve kamu kaynaklarının giderek daha fazla bir bölümünün özel AR-GE faaliyetlerinin desteklenmesine ayrılması, uygulanan

AR-GE destek programlarının üretime, büyümeye ve AR-GE etkinliğine etkilerinin değerlendirilmesi gerekliliğini gündeme getirmiştir.

Teknoloji politikaları üzerine yapılan çalışmalar AR-GE destek programlarının teknolojik gelişmenin hızı ve yönünü etkilemekteki önemli rolünü vurgulamıştır. AR-GE destek programlarının teknoloji faaliyetlerine etkilerini inceleyen ampirik çalışmalar AR-GE desteği alan firmaların AR-GE faaliyetlerine ayırdıkları harcamalarını artırdıkları sonucuna varmışlardır. AR-GE harcamalarındaki bu artış yenilik eğilimini arttırarak firmaların büyümesine ve genel düzeyde ekonomik performansın ve hatta işgücü talebinin artmasına sebep olmaktadır. AR-GE desteklerinin özel AR-GE harcamalarına ve üretim artışına olumlu etkileri literatürde incelenmiş olsada, az sayıda araştırma AR-GE desteklerinin istihdam oluşumu üzerindeki etkilerini incelemiştir.

Bu tezin ilk amacı, teknoloji politika araçlarından biri olan AR-GE destek programlarının araştırmacı talebi üzerindeki etkisini Türk imalat sanayisindeki firmalar için araştırmaktır. Betimsel incelemeler, AR-GE yapan imalat sanayii firmalarının toplam AR-GE yapan firmaların ortalama % 70'ini oluşturduğunu ve bu AR-GE yapan firmaların TTGV ve TİDEB tarafından desteklenenlerinin oranının % 28 olduğunu göstermektedir. Bu destek alan firmalar çoğunlukla orta teknoloji sanayilerinde faaliyet gostermektedirler ve göreceli olarak hem firma düzeyinde hem de sektör düzeyinde AR-GE yoğundurlar. Destek alma durumuna göre, toplam AR-GE personeli içindeki araştırmacı oranı incelendiğinde, AR-GE desteği alan firmaların almayanlara göre daha fazla araştırmacı istihdam ettikleri görülmüş ama AR-GE desteği alan firmaların almayanlara göre araştırmacılara daha fazla ücret ödediklerine dair sağlam bir kanıt bulunamamıştır.

AR-GE desteği almanın araştırmacı talebi üzerindeki etkisi "seçim yanlılığı" (selection bias) sorununu çözen iki kademeli "davranış etkisi" (treatment effect) modeli tahmin edilerek değerlendirilmiştir. İlk olarak, AR-GE desteği almayı belirleyen faktörler firma büyüklüğü, firmanın teknoloji transfer edip etmediği, geçikmeli AR-GE yoğunluğu, kalifiye personel oranı, sektörel AR-GE yoğunluğu, yayılma (spillover) etkisi ve daha önce AR-GE desteği alma durumu gibi açıklayıcı değişkenler kullanılarak tahmin edilmiştir. Daha sonra, arastırmacı talebi için statik ve dinamik modeller, AR-GE desteği almayı dışsal kabul ederek ve araştırmacılara ödenen ücret, girdi ve sermaye fiyatları, ortalama ücret oranı ve

firmanın teknolojik yeteneğini ölçen teknoloji transferi kukla değişkeni gibi açıklayıcı degişkenler kullanılarak tahmin edilmiştir.

Kestirim sonuçları, firma büyüklüğü, geçikmeli AR-GE yoğunluğu, kalifiye personel oranı, sektörel AR-GE yoğunluğu, yayılım ve firmanın daha önce destek alması gibi belirleyicilerin firmaların AR-GE desteği almaları üzerinde olumlu etkileri olduğunu göstermektedir. Ayrıca, AR-GE desteği almanın firmaların araştırmacı talebini arttırmayı teşvik ettiği de bulunmuştur.

Teknolojik büyümeyi AR-GE yoluyla destekleyen ve teşvik eden teknoloji politikaları bütünün sadece bir bölümünü ama önemli bir bölümünü oluşturmaktadır. AR-GE destek programlarının AR-GE'ye harcanan kaynakların etkin dağıtılmasında önemli bir teknoloji politika aracı olarak incelenmesi, bu kamu finansman mekanizmalarının AR-GE faaliyetleri üzerindeki etkisinin araştırılmasını sağlamıştır. Teşvik edilmiş AR-GE faaliyetlerinin firmaların performansına yenilik eğilimlerini arttırmak yoluyla olan katkısı, bütünün diğer önemli bir parçası olarak ayrıca değerlendirilmelidir.

Yenilik bir ülkenin rekabet edebilirliliğini, ekonomik büyüme hızını ve performasını etkileyen en önemli faktörlerden biridir. Neo-klasik yaklaşım uzun bir süre yeniliğin ekonomik değişimdeki rolünü önemsemezken, 1980'lerin ortalarından itibaren yeni büyüme teorisi, yeniliği büyümenin itici gücü olarak algılamaya başlamıştır. Teknolojik ilerlemenin, sürdürülebilir ekonomik büyümenin en önemli anahtarlarından biri olarak kabul edilmesi, yeniliği belirleyen faktörlerin anlaşılmasına odaklanan bir literatür oluşturmuştur.

Yenilik faaliyetlerinin yoğunluğundaki firma ve sanayi düzeyindeki farklılıklar ekonomi yazınında önemsenmiş ve araştırmaların çoğu Schumpeter'in büyük ve piyasa gücü yüksek olan firmaların yeni ürünlerin ve süreçlerin gercekleştirilmesinde belirleyici bir rolü olduğu tanımının genişletilmesi yönünde yapılmıştır. Bu görece dar kapsamlı eğilim, firmaların büyüklüğü ve piyasa yapısı gibi degişkenleri yenilik eğilimini açıklamakta kullanmıştır. Bu değişkenleri kullanarak yapılan çalışmaların sonuçları kesin bir yargıya ulaştırmayınca, talebin yapısı, teknolojik fırsatlar (technological opportunity) ve yeniliğin kazanımlarının kullanılması (appropriability) gibi ölçütler yenilik eğiliminin sanayiler ve firmalar arasında farklılaşmasını açıklayabilmek için birleştirilerek yeni bir literatür oluşmuştur.

Bu tezin ikinci amacı, Türk imalat sanayisindeki firmaların ürün ve süreç yeniliği gerçekleştirme eğilimini belirleyen faktörleri 1995-1997 ve 1998-2000 yılları için analiz etmektir. Betimsel incelemeler, yenilik yapan firmaların oranının 1995-1998 döneminde % 23 ve 1998-2000 döneminde % 30 olduğunu ve bu firmaların çoğunlukla orta ve yüksek teknoloji sanayilerinde faaliyette bulunduklarını göstermektedir. Düşük teknoloji sanayilerinde, süreç yeniliği yapan firmaların oranı ürün yeniliği yapan firmaların oranına göre daha yüksek olduğu ve yüksek teknoliji sanayilerinde bu durumun tam tersi olduğu görülmektedir.

Ürün ve süreç yeniliğini belirleyen faktörler "iki değişkenli probit" (bivariate probit) modeli tahmin edilerek değerlendirilmiştir. Firma büyüklüğü, yaşı ve piyasa yapısını belirleyen yoğunlaşma oranı gibi firma ve sanayi düzeyindeki değişkenler, Schumpeterci geleneksel varsayımı test etmekte kullanılmıştır. Bunlara ek olarak, firmanın teknoloji transfer edip etmediği, kalifiye personel oranı, AR-GE yoğunluğu ve internet kullanım yoğunluğu gibi firmanın teknolojik yeteneğini belirleyen değişkenler de tahmin modeline eklenmiştir. Son olarak, kamu AR-GE finansmanının yenilik eğilimi üzerine etkisini incelemek için firmanın AR-GE desteği alıp almadığı, yenilik eğilimini belirleyen faktörleri belirlemekte kullanılan tahmin modeline eklenmiştir.

Yapılan nicel analizler sonucunda, ürün ve süreç yeniliğini belirleyen faktörlerin birbirleriyle ilgili oldukları fakat sanayinin teknolijik seviyesi ve olanaklarıyla farklılaştıkları bulunmuştur. Firma yaşının, firma büyüklüğünün, AR-GE ve sermaye yoğun olmanın yenilik eğilimine olumlu etkileri yeniliğin çeşidinden ve teknoloji seviyesinden bağımsızdır. Türkiye imalat sanayiinde, yeniliğin çeşidi ve sanayinin teknoloji seviyesi gözetilmeksizin yenilik gerçekleştirmede büyük ve eski firmalar ölçek ekonomisi ve finans sağlama olanaklarından faydalanmaktadırlar. Ayrıca, yenilik yapma eğilimi yoğunlaşmış piyasalarda daha yüksektir. AR-GE faaliyetlerinin yayılımları düşük teknoloji sanayilerinde diğer sanayilere kıyasla daha önemlidir. Son olarak, AR-GE desteği almanın firmaların yenilik eğilimine katkısı olumlu yöndedir ve bu katkı orta ve yüksek teknoloji sanayilerinde daha belirgindir.

Ürün ve süreç yeniliğinin firmalar tarafından uygulanması, firmaların üretim maaliyetlerini, piyasa rekabet edebilirliliğini ve ekonomik performanslarını etkileyerek, firmaların büyümesi ve hayatta kalabilmesi için önemlidir. Yenilik

faaliyetlerinin ekonomik performans üzerindeki etkilerinden biri istihdam oluşumuna katkılarıdır ve bu etki yeniliğin tipine göre farklılaşmaktadır. Ürün yeniliği, ürünün talebini etkileyerek, yenilikçi firmanın piyasa payı ve buna bağlı olarak istihdamı üzerinde olumlu etki oluşturmaktadır. Süreç yeniliklerinin uygulanması maaliyeti yani ürünün arzını etkileyerek, üretkenlikteki artış dolayısıyla işgücü talebinde daralmaya sebep olmaktadır. Bu iki farklı etki, iktisatçıların ve politika yapıcıların teknolojik yeniliğin ekonomik ve sosyal sonuçları üzerinde tartışmalarına sebep olmuştur.

Bu tezin son amacı, Türk imalat sanayisinde ürün ve süreç yeniliğinin istihdam üzerindeki etkilerini 1995-1997 ve 1998-2000 yılları için incelemektir. Betimsel incelemeler, sanayilerin teknoloji seviyesi gözetilmeksizin, yeniliğin istihdam üzerinde olumlu etkileri olduğunu vurgulamaktadır.

Ürün ve süreç yeniliğinin istihdam üzerinde farklı etkileri olduğunu varsayarak, bu varsayım iki farklı ekonometrik model kullanılarak tahmin edilmiştir. Birinci model yeniliğin dışsallığını kontrol eden "davranış etkisi" tahmin yöntemidir. Bu modelin ilk kademesi ürün ve süreç yeniliğini belirleyen faktörlerin "iki değişkenli probit" modelini kullanarak daha önce ikinci analizde kullanılan açıklayıcı değişkenler ile tahmin edilmesinde oluşmaktadır. İkinci kademede, istihdamın büyüme hızı, ürün ve süreç yeniliği yapmayı dışsal kabul ederek, büyüklük, yaş ve ortalama ücret gibi firma düzeyindeki değişkenlerle, yoğunlaşma oranı ve sektörel çıktı büyüme hızı gibi sanayi düzeyindeki değişkenler kullanılarak tahmin edilmiştir. Bunlara ek olarak, firmanın teknolojik yeteneğini belirleyen teknoloji transferi ve kalifiye personel oranı gibi değişkenlerle, ürün ve süreç yeniliği gerçekleştiren firmaların büyüklüğü ve yaşı gibi ölçütler, istihdam modelinin tahmininde kullanılmıştır.

Sanayilerin teknolojik düzeyleri gözetilmeksizin ürün yeniliğinin istihdam üzerindeki etkisi olumsuz ve süreç yeniliğinin istihdam üzerindeki etkisi olumlu olarak bulunmuştur. Ayrıca, ürün ve süreç yeniliğinin istihdam üzerindeki etkileri firma büyüklüğü arttıkça güçlenmektedir. Bu sonuçlar daha önceki ampirik çalışmalarda gözlemlenen ürün yeniliğinin istihdam üzerindeki olumlu etkileri ve süreç yeniliğinin istihdam üzerindeki olumsuz etkileriyle çelişmektedir. Bu sonuçlar, süreç yeniliğinin istihdam üzerindeki etkilerini dengeleyici telafi mekanizmalarının (compensation mechanisms) Türkiye özelinde çalıştığını

göstermektedir. Sektörel düzeyde, ürün yeniliği ürünün talebini etkileyerek, işgücü talebini arttırır. Ama, ekonomik düzeyde istihdam, bütün sektörlerin kendi aralarında etkileşimleri ve talep ve arz koşullarının etkileşmesine dayanmaktadır. Ayrıca, Türkiye'de geliştirilen yeni bir ürün girdi olarak daha az işgücü kullanmayı gerektirmektedir ve buna bağlı olarak işgücü talebi firma ve sektör düzeyinde bu özel durumda azalmaktadır.

İkinci model firmaların faaliyetlerine devam ediyor olmalarını kontrol eden bir "seçim" (selection) modelidir. Yeniliğin istihdam üzerine uzun süreli etkilerini firmanın 2000 yılında kapanmamış olma şartını gözeterek tahmin etmek için kullanılan bu seçim modelinin ilk kademesinde firmaların faaliyetlerine devam etme olasılıklarını belirleyen faktörler, firma büyüklüğü, yaşı, işgücü hareketliliği, işgücü üretkenliği, sermaye yoğunlugu, borçluluk oranı ve yoğunlaşma oranı gibi açıklayıcı degişkenler kullanılarak tahmin edilmiştir. Ikinci kademede, istihdamın büyüme hızı 2000 yılına kadar faaliyetine devam eden firmalar için daha önce kullanılan açıklayıcı degişkenlerle tahmin edilmiştir.

Firmaların faaliyetlerine devam etme ihtimalleri firma büyüklüğü ve sermaye yoğunluğuna bağlı olarak bütün teknoloji seviyelerinde artmaktadır. Ayrıca, düşük teknoloji sanayilerinde yeni firmaların faaliyetlerine devam etme ihtimalleri daha yüksekken, orta ve yüksek teknoloji sanayilerinde eski firmaların hayatta kalma şansı daha yüksektir. Düşük teknoloji sanayilerinde ürün yeniliği yapmak firmaların faaliyetlerine devam etme ihtimallerini azaltırken, süreç yeniliği yapmak bu ihtimali arttırmaktadır. Orta ve yüksek teknoloji sanayilerinde ise tersi bir durum gözlemlenmektedir. Bunun arkasındaki muhtemel sebep düşük teknolojili firmaların faaliyetlerine devam etme şanslarının ancak süreç yeniliği ile ulaşılabilen fiyatlarda rekabet edebilirliğe dayanırken, orta ve yüksek teknolojili firmaların hayatta kalma stratejilerinin ürün yeniliği ile ulaşılabilen teknolojik rekabet edebilirliklerine dayanmasıdır. Faaliyetlerine devam eden firmaların istihdam büyüme hızları ile ilgili kestirim sonuçlarını incelediğimizde, ürün yeniliğinin istihdam üzerinde etkisi düşük teknoloji sanayilerinde olumlu iken, bu etki orta ve yüksek teknoloji sanayilerinde olumsuz yöndedir.

Türkiye'de AR-GE desteği alan firmaların oranı gelişmekte olan ülkelere nazaran daha düşük olmasına rağmen, AR-GE desteği almanın AR-GE faaliyetleri üzerinde olumlu bir etkisi vurgulanmıştır. AR-GE desteğinin faydaları araştırmacı

talebinin arttırılması ile kazanılmaktadır. Türk imalat sanayilerinin yenilik eğilimlerine bakıldığında düşük teknoloji sanayilerinin süreç yeniliği yapma eğiliminde, orta ve yüksek teknoloji sanayilerinin ürün yeniliği yapma eğiliminde oldukları gözlenmektedir. AR-GE destekleri, düşük teknoloji sanayilerinde süreç yeniliği yapma eğiliminine olumlu katkıda bulunurken, orta ve yüksek teknoloji sanayilerinde ise ürün yeniliği yapma eğiliminde önemli bir rol oynamaktadır. Firma büyüklüğü ve yaşının yenilik yapma eğilimindeki rolü ile ilgili bulgular hali hazırda görülen Schumpeterci varsayımları test eden ampirik çalışmaları desteklemektedir. Firmaların teknolojik fırsatlarının ve kabiliyetlerinin kendileri de değişime tabi olmalarına rağmen, bu koşullar sanayiler arası yenilik faaliyetlerinde görülen farklılıkları açıklamada önemlidir. Bu nedenle, firma büyüklüğü ve piyasa yoğunluğunun önemini vurgulayan dar bakış açısından, firmaların teknolojik farklılıklarını, yeniliğin kazanımlarını ve talebin yapısını vurgulayan daha geniş bir bakış açısına yönelim sanayi düzeyindeki farklılıkların kaynaklarını çok daha etkin bir şekilde tanımlayarak açıklamaktadır. Düşük teknoloji sanayilerinde yeniliğin daha yüksek bir istihdam büyüme hızı yaratması yeniliğin, bu sanayilerde ekonomik performansın belirlenmesinde daha etkili olduğunu göstermektedir. Son olarak, yeniliğinin istihdam üzerindeki etkilerini ürün ve süreç yenilikleri için ayırarak incelemenin önemli olduğu ve toplam talebin ve makroekonomik koşulların dengeleyici telafi mekanizmalarıyla birlikte yeniliğin istihdam üzerinde olumlu etkiler yaratmada önemli bir rol oynadığı söylenebilir.

APPENDIX C

CURRICULUM VITAE

Personal Information

Surname, Name: Üçdoğruk, Yeşim
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Education

MSc in Economics – January, 2001, Department of Economics, Middle East Technical University, Ankara, Turkey (Thesis Title: Does the Turkish Social Security Systems Perform its Functions? A Case Study: SSK; Thesis Supervisor: Assoc. Prof. Cem Somel).

BSc in Economics – June, 1998, Department of Economics, Middle East Technical University, Ankara, Turkey.
High School – June, 1994, Sırrı Yırcalı Anadolu High School, Balıkesir, Turkey.

Employment Record

1998 – 2005: *Teaching & Research Assistant*, Department of Economics, Middle East Technical University, Ankara, Turkey.

Fields of Academic Interest

Economics of Innovation & Technology
Industrial Economics
International Economics

Conference Presentations

"Do researchers benefit from R&D support programs in Turkey?", paper presented at SMYE Conference, Geneva, Switzerland, April 22-24, 2004 (funded by METU).

"Do researchers benefit from R&D support programs?", paper presented at SPRU PRIME Doctoral Conference, Brighton, UK, May 19-20, 2004 (partially funded by SPRU).

"Dynamics of entry and exit in Turkish Manufacturing Industry" (together with Seçil Kaya), paper presented at International Conference in Economics

VI, Economic Research Center (ERC), Middle East Technical University, Ankara, Turkey, September 11-14, 2002.

Working Papers

"The dynamics of entry and exit in Turkish manufacturing industry" (together with Seçil Kaya), ERC Working paper No: 02/02.

Teaching Experience

2005: *Recitation Assistant*: Econ 354: Introduction to International Economics II, Department of Economics, Middle East Technical University, Ankara, Turkey.

2004: *Recitation Assistant*: Econ 353: Introduction to International Economics I, Department of Economics, Middle East Technical University, Ankara, Turkey.

2004: *Recitation Assistant*: Econ 202: Macroeconomic Theory, Department of Economics, Middle East Technical University, Ankara, Turkey.

2002: *Recitation Assistant*: Econ 502: Macroeconomic Theory I, Department of Economics, Middle East Technical University, Ankara, Turkey.

2001: *Recitation Assistant*: Econ 102: Introduction to Economics II, Department of Economics, Middle East Technical University, Ankara, Turkey.

2001: *Recitation Assistant*: Econ 101: Introduction to Economics I, Department of Economics, Middle East Technical University, Ankara, Turkey.

1997 – 1998: S*tudent Assistant*: Econ 301: Introduction to Econometrics I, Department of Economics, Middle East Technical University, Ankara, Turkey.