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KRISTIINA HUTTUNEN

Empirical Studies on Labour Demand, Wages and Job Displacements

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Kristiina Huttunen

Contents

I Introduction

1 Background

The structure of wages and employment has dramatically shifted in many countries in recent years. There has been a clear increase in demand for better educated workers throughout the Western economies. In United States this has taken a form of an increasingly unequal distribution in earnings, whereas in continental Europe it has resulted in dramatic rise in joblessness. The sources of these trends have been the subject of much study. Many researchers believe that the shift in labour demand is explained by recent changes in firms' production technology, such as the adoption of new machinery and information technology in firms' production processes. The main idea behind this explanation is that skilled workers have a better capacity to adapt to changing economic conditions and that new technologies are more complementary to skilled workers than to unskilled workers. There are number of studies which show empirical evidence that supports this hypothesis of *skill-biased technological change*[1].

Skill-biased technological change is not the only possible explanation for the increase in the demand for skilled labour. There are a growing number of studies that examine whether increased *globalization* can be offered as an alternative explanation for the rapid rate of skill upgrading found in the US

[1]See e.g. Berman et al., 1994, 1998, Machin et al., 1998, and for a survey, Chennels and Van Reenen, 1999.

and elsewhere[2]. A traditional trade theory suggests that increased trade of final products can lead to changes in production share between countries so that countries that are abundant in skilled labour would specialize in the production of skill-intensive products and hence the demand for skilled labour would increase as the employment within skill-intensive sectors grows[3]. Internationalization can also affect the demand for skills through intermediate input markets by foreign outsourcing[4]. Firms in industrial countries facing higher relative wages for unskilled labour than that found abroad, outsource activities that use a large amount of unskilled labour. Moving these activities overseas will reduce the relative demand for unskilled labour in the country, in much the same way as replacing these workers with automated production.

One aspect of globalization is the growing number of *foreign-owned firms* in domestic markets. Several studies have found that foreign-owned firms differ substantially from domestic firms. Foreign-owned firms are larger, more productive, more skill-intensive and pay higher wages.[5] This might be simply the result of selection of high wage or skill-intensive establishments for acquisition by foreign firms, or the acquisition itself might have an effect on the skill demand and wages of domestic establishments. The modern theory of multinational enterprises (MNEs) suggests that foreign-owned firms are different from domestic-owned firms simply because they need to be different. If foreign multinational enterprises are exactly identical to domestic firms, they will not find it profitable to enter the domestic market. Foreign firms presumably operates against disadvantages such as inferior knowledge of local markets and tastes and inferior connections with local politicians and financial institutions. In order to overcome these drawbacks, the foreign firm must possess some firm-specific advantages, such as superior technology, marketing and managing skills, or export contacts, that overcome the

[2] See Feenstra and Hanson (2001), for a survey.
[3] See e.g. Ethier, 1984.
[4] See e.g. Feenstra and Hanson, 1996.
[5] See e.g. Blonigen and Slaughter, 2001, Conyon, Girma, Thompson and Wright, 2002.

inherent advantages of local firms[6]

If multinationals do indeed possess such assets, then we would expect the recent increase in the foreign direct investments and foreign-owned firms to have important contributions on employment and wages of different skill groups in domestic market. Most of the foreign investments flows are between pairs of developed countries (Markusen, 1995). Theory does not provide a direct answer to the question what is the effect foreign-ownership on the relative wages and skill demand between countries of similar skill-mix. So far only a few empirical studies have examined directly how increased foreign-affiliate activity has contributed to changes in skill demand and wage inequality[7].

Globalization and technological change might lead to important restructuring, which causes many workers to loose their current jobs[8]. This is especially likely to happen in countries with lower degree of downward flexibility in wages. The costs of this restructuring depend on how long lasting are the consequences of job loss for displaced workers. Several studies have tried to quantify the costs imposed on workers who are displaced from their jobs in United States[9]. Majority of the studies (e.g. Jacobson, Sullivan and Lalonde, 1993, Stevens, 1997) indicate that the earnings and employment losses of displaced workers are large and persistent. Less sure is, however, what explains these losses and whether they are equal to all workers. The number of studies on displaced workers in Europe is much more limited and the results less clear (e.g. Bender et al. 2002). There is however a clear need to understand whether the experiences of displaced workers in US are typical for other developed countries and whether the possible differences be-

[6] See e.g. Caves, 1996, Markusen 1995, Aitken and Harrison, 1996, and Bloningen and Slaughter, 2001.

[7] See Feenstra and Hanson, 1997, Bloningen and Slaughter, 2001, and Taylor and Driffield, 2004

[8] Addison et al. (2000) provide evidence that workers employed in industries with elevated import shares and high levels of investment in computers appear to have increased rates of job loss. White (2002) finds that increased import competition has significant effects on industry-level displacement rates in US manufacturing.

[9] See surveys by Fallick, 1996, and Kletzer 1998.

tween different countries reveal some fundamental information of functioning of different type of economies.

The job displacement might have very different consequences for different type of people. Older workers and workers with longer pre-displacement job tenure are expected to loose more since their human capital is mostly firm-specific. Education might play important role as well. Highly educated workers are assumed to have more transferable human capital and so they may loose less from displacement and recover more rapidly. So far only few studies have examined how worker's educational level affect the magnitude of these losses[10].

The costs of job displacement also depend on the fact, whether a worker has time and possibility to react before the job is destroyed[11]. When entire plant is being closed down both workers and the firm have normally time to react before the actual closing down occurs. The knowledge of future closure will influence both firm's hiring and firing decisions, as well as the workers' quitting decisions. The firm chooses to retain its most productive workers, while workers with relatively better external market opportunities and lower proportion of firm-specific human capital are more likely to quit. This means that there is an important selection process going on in the firm before the actual closing down occurs. This selection process is likely to affect the post-displacement outcomes of the workers: The ones who leave voluntarily from these plants are not expected suffer any losses at all, while the ones who are laid off before the closure occurs, or the ones who choose to remain with their plant until the end are expected to be worse off. One reason why the type of job loss might matter, is that market makes inference on worker's unobserved ability by the behavior of their former employer[12]. Firm's desire to retain

[10] See Stevens (1997), Farber (1997) Kletzer (1989, 2001).

[11] Several studies have shown that advance notice reduces workers post-employment earnings and employment losses. See e.g. Addison and Portugal (1987), Ruhm (1994) and Friesen (1997).

[12] See Gibbons and Katz, 1991 and Farber and Gibbons, 1996.

a worker signals to the market that worker is of high ability. Consequently, the market infers that laid-off workers are of low ability. Assuming that no such negative inference is warranted if workers are displaced in plant closing, post-displacement wages should be lower for those who were laid off before the plant closing down occurred, than for those who remained with the dying plant until the end.

This doctoral dissertation examines in detail the consequences of technological change and globalization on Nordic labour markets. The goal is to provide evidence how these changes affect employment and wages of different skill groups. In addition we analyze what happens to the workers who loose their jobs in this process. That is, we analyze how severe earnings and employment reductions workers suffer after being displaced from their jobs. The thesis consists of four independent essays. The first two essays use plant-level panel data with detailed worker characteristics from Finland. These two essays examine the effect of technological change and globalization on skill demand and wages in Finland during 1988-2001. The third and fourth essay utilize unique linked employer-employee panel data from Norway for 1988-2000. These essays examine the consequences of job displacement. The aim is to explore how severe earnings and employment losses workers suffer after job displacement in Norway, and how these losses differ between different type of workers.

2 Contents of the Dissertation

2.1 R&D-activity, Exports, and Changes in the Skill Demand in Finland

The first paper of my thesis examines empirically whether the increased export- and R&D-activity were associated with changes in the skill structure of labour demand in Finland during 1988-2001. During this period Finland went trough significant changes. The early part of 1990's was marked by exceptionally severe recession. A recovery period was associated with a rapid re-structuring of the economy, which was induced by a growth of new export-oriented more technologically advanced industries. These changes are assumed to reflect higher rate of technological change and increased globalization of the economy. This period in Finland provides us thus an interesting case to examine the effects of technological change and globalization on labour market.

Worker's skill level is defined by both education and age. Technological change and trade are expected to increase the demand for highly educated workers. Technological progress might also change the relative demand for workers in different age groups: If the skills of older workers are of an older vintage, the technological process is likely to make them obsolete more quickly. If this is true, the hypothesis of highly educated having a better capacity to adapt to recent changes in production would not hold for older workers.

The study uses unique establishment-level panel data with linked information on worker characteristics from Finland for 1988-2001. The empirical analysis consists of two parts. In the first part we rely on panel data on Finnish private sector establishments and analyze the recent changes in the wage bill and employment shares of different skill groups. The aggregate change is further decomposed into changes that have occurred *within* establishments, *between* establishments, and due to entry and exit of establishments. In the second part we regress the establishment level wage bill share equations of different skill groups on observable trade and technology indicators. This method provides us with a way to examine the direct impact of these variables on the changes in the skill mix of labour demand that have occurred *within* establishments.

The analysis provides evidence that the skill structure of the Finnish private sector establishments' work force has shifted towards highly educated and older workers, closely reflecting the changes in the skill structure of the population. The increase in the share of both highly and less educated older workers has mainly occurred within establishments while the increase in the share of highly educated younger workers has occurred between establishments and by the entry of new establishments. The estimation results without plant controls show that plants with high level of R&D and exports employ more highly educated younger workers, while the impact of these variable is much less pronounced or even insignificant for highly educated older workers. However, the fixed effects estimation results provide no evidence that an increase in the level of R&D intensity and export share would affect the changes in skill demand within establishments.

2.2 The Effect of Foreign Acquisition on Wages and Skill Composition

The second study of the thesis examines the effect of foreign acquisition on employment and wages of different skill groups in Finland. The aim is, in particular, to examine whether there are significant differences on the effect of foreign acquisition on wages and employment of workers from different skill groups. Moreover, we aim to put significant effort to examine whether the relationship between foreign ownership and wages or employment is simply a correlation or whether foreign acquisition itself has an effect on the wages and on the skill mix of plant's work force.

We use plant-level panel data with matched information on worker characteristics from Finnish manufacturing for the years 1988-2001. During this period Finland experienced a high increase in the share of foreign-owned plants. This increase might reflect both the global increase in foreign direct investments and acquisitions, and the big changes that Finnish economy went trough the period: exceptionally severe recession in early 1990's, that was associated with a rapid re-structuring of the economy, and the joining of the European Union in 1995.

We aim to improve the previous literature in three ways: First, we use unique plant-level panel data with matched information on employee characteristics *by skill groups*. These data allow us to examine whether the effect of foreign acquisition on employment and wages varies by the educational level of the workers. In addition, the data allow us to control for rich set of pre-acquisition characteristics of the plants, including a large number of employee characteristics, and thus to study whether the change in the ownership might influence the changes in the average characteristics of plant's employees. We can thus disentangle the effect of foreign ownership on wages from the effect on the quality of the labour force.

Second, in addition to standard regression techniques we use various propensity score matching methods, including difference-in differences matching introduced in Heckman, Ichimura and Todd (1997). The central idea in the matching methods is to base the estimation on a very careful matching of cases and controls using a rich set of observable characteristics. This is a way to make sure we use a suitable comparison group and take into account all the possible factors that affect the possible selection of plants for acquisition by foreign firm.

Third, the changes in employment and wages that are caused by foreign acquisition might not happen instantaneously. It is well known that there are important costs in both hiring and firing of workers, and these costs might vary by the skill level of the workers. These adjustment costs mean that changes in labour demand or in average wages do not happen instantly. We take this into account and examine the effect of foreign acquisition on wages and employment in different periods after acquisition.

The results from both matching and regression indicate that foreign acquisition has a positive effect on wages of all skill groups in domestic plants. The wage increase is not immediate, but happens within 1-3 years from the acquisition. The magnitude of this effect increases with the level of schooling of the workers. The result of the employment effect are less clear. The regression analysis using the whole sample indicates that foreign acquisition does not have an effect on the share of highly educated workers in plant's workforce. However, the matching results indicate that acquired plants reduce, although slightly and slowly, the share of highly educated workers in their employment. Thus, it seems that foreign owners decrease the number of highly educated workers in their new plants, but the ones who remain are paid clearly more than the ones whose plants remained domestically-owned.

2.3 How Destructive is Creative Destruction? The Costs of Worker Displacements

The third paper of the thesis analyzes the costs of worker displacement in Norway. Specifically, we seek to determine how severe and long-lasting are the employment and earning losses of people who loose their jobs due to plant closing down or significant downsizing. We use large administrative matched employer-employee data set for the years 1986-2000.

One novelties in the paper is that we can follow workers and their earnings even if they leave the labour force. We argue that in order to examine the true costs of displacement, it is important to work on population data, because displacement might have an impact on the probability of leaving the labour force permanently. It is also important to allow workers in the comparison group to leave the labour force. This group represents the "ongoing economy", and a significant number of workers leave the labour force for reasons other than having been displaced.

In addition to estimating the average effects of displacement, we analyze heterogeneity in displacement effects by observable pre-displacement worker, plant, and labour market characteristics. Are old workers more vulnerable than young workers? What happens to workers displaced from plants in industries with negative long term growth? What happens to workers that are displaced from firms which are dominant in a local labour market? When examining effects by pre-displacement characteristics, we can better understand the reasons behind displacement costs. Furthermore, we also allow the displacement effects vary by the type of separation. That is, we divide our "treatment group", displaced workers, into three different subcategories: workers who were laid off when the plant closed down, workers who separated from these plants in a period before the closure occurred, and workers who were displaced due to significant downsizing of a continuous plant.

We find that displacement significantly increases the probability of leaving the labour force. Those displaced workers who find re-employment work on average 3.2 months less in the following year as compared to similar workers who were not displaced. Seven years after displacement the average employment reduction is only a few days per year. Earnings is on average reduced by 2-5 percent in the first year after displacement. This effect decreases slowly, and is 1-2 percent seven year after displacement. The negative employment effect is in the short run weaker for workers that were displaced by plant closure than for those displaced from downsizing firms. This is consistent with the latter group searching less intensely for a new job because they hope to be recalled. We find that workers with less than 10 years of schooling, and workers displaced from small plants are more vulnerable than other groups. Age and tenure have surprisingly little impact on the consequences of displacement.

2.4 Worker Turnover in Dying Plants and Re-employment Wages

The fourth paper of the thesis examines worker turnover in dying plants using matched employer-employee data from Norway for 1988-2000. The aim is to find out whether there are differences in the re-employment wages and post-displacement earning losses of the workers who leave the firm at different stages. The hypothesis is that the knowledge of future economic distress will influence both firm's hiring and firing decisions, as well as the workers' quitting decisions. The firm chooses to retain its most productive workers, while workers with relatively better external market opportunities and lower proportion of firm-specific human capital are more likely to quit. This process will make the skill distribution of plant's workforce more compressed, as the worse and best workers are more likely to separate from these plants.

The empirical analysis can be divided into two parts. First, we examine whether there are significant changes in the workforce skill distribution before the plant closure and whether workers who leave the dying plants in different stages differ significantly by their observable characteristics. Second, we examine whether there are significant differences in the post-displacement earning losses of workers who leave the dying plant in different stages. This allows us to study whether this selection process in dying plants affects the magnitude of post-displacement earnings losses.

The theoretical framework is based on the assumption that when a negative shock arrives both workers and firms engage in strategic behavior. The market infers their behavior and assign the re-employment wages accordingly. The framework yields two empirically testable predictions: (1) In the period before the plant is shut down there are significant changes in the workforce skill distribution. (2) Workers' re-employment wages and post-displacement earning losses differ between workers who leave the dying plant in different stages.

The results are consistent with the theoretical framework. There are significant changes in the workforce skill distribution before the plant closure. Workers who decide to leave the dying plant early suffer no wage losses in their re-employment jobs, while the ones who stay until the end suffer significant earning losses. On the other hand, workers who are laid off in the period before the plant's death suffer even more severe earnings reductions, than the ones who were laid off during the period when the closure occurred.

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II R&D-activity, Exports, and Changes in the Skill Demand in Finland

Abstract

During 1990's Finnish economy experienced a rapid increase in exports and R&D activity. This paper investigates the impact of these phenomena on the skill structure of labour demand, using panel data on Finnish establishments for 1988-2001. The worker's skill level is defined by both education and age. The results indicate that despite the general shift in employment towards highly educated and older workers, the selected technology and trade indicators, R&D intensity, and export share, did not have significant effect on the changes in the skill demand within manufacturing sector plants in Finland during the period.

1 Introduction

It has been well established that there is a clear shift in demand towards better educated workers throughout the Western economies. The size and timing of labour demand shifts have led many researchers to believe that the shift is explained by recent changes in firms' production technology, such as the adoption of new machinery and information technology in firms' production processes. There are number of studies which show empirical evidence that supports this hypothesis of *skill-biased technological change* (see Chennels and Van Reenen, 1999, for a survey). Another often used explanation for skill upgrading is the increase in international trade, generating a shift in product demand towards more skill-intensive products (e.g. Feenstra and Hanson, 1996).

Finnish economy has gone through significant changes during the last 15 years. The early part of 1990's was marked by exceptionally severe recession, where unemployment rate rose from 3 percent in 1990 to 17 percent in 1994. The recovery period was associated with a rapid re-structuring of the economy, which was induced by a growth of new export-oriented more technologically advanced industries. These changes are assumed to reflect higher rate of technological change and increased globalization of the economy. This period in Finland provides us thus an interesting case to examine the effects of technological change and globalization on labour market.

This study examines empirically whether the increase in exports and R&D activity were associated with changes in the skill structure of labour demand in Finland during the period. The major difference between this study and the previous studies is that worker's skill level is defined by both education and age. Most of the previous studies that examine the impact of technological change on skill demand use a very crude definition of skill: typically labour is divided into only two groups by some educational level or by division of labour into production and non-production workers. However, human capital theory suggests that a worker's productivity depends on both his educational level and work experience. In addition, technological progress might have a different impact on different skill groups' productivity: If the skills of older workers are of an older vintage, the technological process is likely to make them obsolete more quickly. If this is true, the hypothesis of highly educated having a better capacity to adapt to recent changes in production would not hold for older workers.

The study uses unique establishment-level panel data with linked information on worker characteristics from Finland for 1988-2001. The empirical analysis consists of two parts. In the first part we rely on panel data on Finnish private sector establishments and analyze the recent changes in the wage bill and employment shares of different skill groups. The aggregate change is further decomposed into changes that have occurred *within* establishments, *between* establishments, and due to entry and exit of establishments. In the second part we regress the establishment level wage bill share equations of different skill groups on observable trade and technology indicators. This method provides us with a way to examine the direct impact of these variables on the changes in the skill mix of labour demand that have occurred *within* establishments.

The analysis provides evidence that the skill structure of the Finnish private sector establishments' work force has shifted towards highly educated and older workers, closely reflecting the changes in the skill structure of the population. The increase in the share of both highly and less educated older workers has mainly occurred within establishments while the increase in the share of highly educated younger workers has occurred between establishments and by the entry of new establishments. The estimation results without plant controls show that plants with high level of R&D and exports employ more highly educated younger workers, while the impact of these variable is much less pronounced or even insignificant for highly educated older workers. However, the fixed effects estimation results provide no evidence that an increase in the level of R&D intensity and export share would affect the changes in skill demand within establishments.

The paper is organized as follows: Next section briefly describes the theoretical background for the analysis. Third section presents the data sets. Fourth section provides descriptive information on changes of the skill structure of labour demand and supply in Finland and the results of the decomposition analysis. Fifth section presents the estimated model. Sixth section provides estimation results of regressions on the effect of observable technology and trade variables on establishments' skill structure. Last section concludes the paper.

2 Theoretical Framework

The analysis is based on the assumption of a profit-maximizing firm, which chooses the level of employment in a static framework. Workers with different levels of education and experience differ in their productivity and they are imperfect substitutes in production. The cost function can be written as

$$C = c(Y, W_{11}, ...W_{nm}, K, \mathbf{T}) \tag{1}$$

where C is total cost, Y is output, W_{ij} is the relative wage of the worker in the age group i with the educational level j, K is capital, and $\mathbf{T}$ a vector of all 'structural variables' that shift the production function and therefore affect costs. Capital is assumed to be fixed in the short run. The associated optimal skill mix M, which describes the optimal combination of different labour inputs in production, can be determined by short run cost minimization for the given level of production Y, while treating capital and the structural factors included in T as exogenous. The optimal skill mix can be written as

$$M = m(\mathbf{T}, K, \mathbf{W}, Y) \tag{2}$$

where $\mathbf{W}$ is the vector of relative wages for labour inputs. $\mathbf{T}$ describes technological change. It captures all structural factors that change the optimal skill mix within firms. That is, it can reflect both the changes in firm's production process (i.e. adoption of new technology and organizational changes in production) as well as the factors that reflect changes in product demand (i.e. increased trade).

This study uses a very broad definition of technological change: it is viewed as a process that encompasses a broad range of changes in the production and organizational structure of a plant, such as the adoption of new machinery, changes in the organization structure of a firm and changes in job requirements (see Bresnahan et al., 2002). How does technological change affect the relative demand for workers from different age and educational groups? We assume that technological progress has a different impact on the productivity of workers with different age and educational levels. Following Nelson and Phelps (1966), we suggest that the rate of return to education is greater, the more technologically progressive the economy is. The basic explanation behind this idea is that education enhances one's ability to receive, decode, and understand information. As explained above, technological progress is assumed to involve various firm-level changes and better educated individuals are assumed to have a better capacity to adapt to these changes. Hence, technological progress is likely to raise the relative productivity of highly educated workers.

Furthermore, we assume that technological change has a different impact on the productivity of workers from different age groups with the same level of education. This idea can be related to vintage human capital literature (Chari and Hopenhayen, 1991, Mac Donald and Weisbach, 2001). The basic assumption behind the vintage human capital model is that skills are acquired by working in a firm using a particular technology and that technology is vintage specific. Human capital that is acquired by working with certain technology is also vintage specific as it is specific to existing technology. As technology evolves, the value of human capital of older workers is eroded as the human capital of older workers is specific to pre-existing technology. In other words, the more rapid the rate of technological change is, the more rapidly older workers skills become obsolete. In addition, by the similar logic as in the vintage human capital literature, technological progress might erode the skills acquired by education as well. That is, as stated in Bartel and Lichtenberg (1987), there might be depreciation of the value of education, so that individuals educated a long time ago do not have a better capacity to adjust to changes in production than their less educated age mates.

Putting these assumptions together, we expect technological change to increase the relative productivity of highly educated workers, but the rise is lower among older age groups, because technological change increases the rate of depreciation of human capital. In other words, if skills of older workers are of an older vintage, technological process is more likely to make them obsolete. This would imply that the hypothesis regarding the superior ability of educated workers to adapt to new technology does not hold for older workers in the same way as it does for younger workers and for the total population.

3 Data

The study uses four different data sources. The main data source is the *Plant Level Employment Statistics Data on Average Characteristics (PESA)*. It is a longitudinal data on Finnish establishments, with linked information on worker characteristics aggregated on the establishment level by skill groups. The linked worker-establishment data are constructed by linking data on workers in the Employment Statistics database of Statistics Finland to data on plants of Business Registers and Industrial Statistics. The data set covers all the private sector establishments (except traffic and construction) with more than two workers. The time period is 1988-2001. The number of establishments is around 50 000 each year. Employees are aggregated into 70 different skill groups by education, age and sex. The data contains information on aggregate worker characteristics for each skill group. The most important variables at the establishment level by skill groups (average in skill group) are: number of people, monthly wage, general working experience, tenure and education. The data set does not have any specific information on establishment characteristics. However, each enterprise and its plant, has a unique identification code, which can be used to match additional information from other statistics and registers on the linked worker-plant database.

Another major data source used in the analysis is the *Longitudinal Data on Plants in Manufacturing (LDPM),* which is constructed especially for research purposes from Annual Industry Statistics. For the period 1974-1994 it covers all manufacturing sector plants with more than 5 workers and for the period 1995-2001 it covers the plants of firms employing at least 20 persons. The number of plants varies between 8000 and 3000 each year. Because of the different plant coverage the number of plants in the sample is considerable smaller in the years 1995-2001. The data set contains information on various plant characteristics, such as size, real value added, gross output, real capital stock, sales, exports and the share of foreign ownership.

Information on R&D investments is collected from two different sources. The first source is the *R&D statistics* of Statistics Finland. R&D statistics is formed by linking together R&D surveys from the years 1991-2001. The R&D surveys contain information on the R&D activities of firms, such as expenditure and number of R&D personnel. The sampling varies from year to year. Basically it covers most of the larger firms, which employ at least 100 persons and the firms which are expected to have R&D activity. The number of establishments each year varies from 1000 to 2000.

For the purpose of our analysis we form two different data sets by linking the different data sources described above. The first data set is formed by linking the PESA data set with LDPM data. As the LDPM data set for the years 1995-2001 consists only the plants of firms that employ at least 20 persons, the number of observations per year is considerably smaller after 1994. For the estimations we restrict the sample to cover only plants of the firms which employ at least 20 workers. The linked data set covers the years 1988-2001 and consists of 41 164 observations. The second data set is formed by linking PESA, LDPM and R&D statistics together. The number of observations in this R&D sample is 18 319. The data set covers the years 1991-2001.

The main variables describing the employee characteristics are obtained from the PESA data set. The focus is on three variables: the monthly wage, employment and the wage bill share. *Employment* describes the number of workers in a skill group working in an establishment during the last week of the year. The average monthly *wage* is calculated as the skill group average of the average monthly wages of individual workers who were employed in the establishment during the last week of the year. The average monthly wage for each individual employed is calculated by dividing the annual wage income by months of employment. The monthly *wage bill* for each skill group is formed by multiplying the average monthly wage of the skill group by the number of workers in the skill group employed in the establishment during the last week of the year.

Variables describing the plant characteristics are from the LDPM data set. The general plant characteristics variables needed in our analysis are real value added and real capital stock. As a *real value added* variable we use a variable that describes the real industrial value added. It is obtained by subtracting all the material inputs and the industrial services from the gross industrial output and deflating with the industry-level price indexes (1995 prices). The *real capital stock* variable is an estimated real value of capital and equipment. Nominal investments are deflated (1995 prices) *using the perpertual inventory method* by implicit industrial price indexes from National accounts (see Maliranta, 1997). The *export-share* ratio is used to proxy internationalization. It is formed by dividing the value of exported shipments by total shipments. Both of these plant level variables are obtained from the LDPM database. The major variable for the "technology level" is a firm-level *R&D/sales ratio* obtained from the R&D statistics. It is calculated by dividing the firm's R&D expenditure by the firm's total sales.

4 Recent Trends in Finland

4.1 Aggregate Changes

The period from 1988 to 2001 was marked with several exceptional phenomena in Finland. During the early 1990 Finland experienced several adverse economic shocks, including the end of eastern trade induced by the collapse of Soviet Union, which led to exceptionally severe recession. The recession hit all the industries and regions and affected workers in all skill groups. The total unemployment rate rapidly from 3 % to 18% within three years (see figure 1.). The period was also marked by a significant changes in the production structure. The recovery period was marked a growth of new industries: namely of export oriented high-tech manufacturing sector. Both the level of exports and R&D activity increased rapidly during the period (see figures 2. and 3.).

During the period, the skill structure of both supply and demand for labour changed. Figures 1-3 plot aggregate shares of four different skill groups in the Finnish working age (15-64-year old) population and in the total wage bill and employment of Finnish private sector establishments[1]. Information on population shares comes from Statistics Finland's population statistics.

[1] Throughout this study, we use a fraction of the wage bill going to different skill groups as a primary measure of labour demand, as it is assumed to reflect changes in *net* demand better. Changes in net demand for different skill groups lead to changes in both wages and employment. An increase in net demand for a certain skill group can generate an increase in the relative wage for this skill group, which in turn could mitigate or even eliminate the positive impact of net demand changes on employment. Similarly, an increase in the relative supply of one group can lead to a reduction in the relative wage of that group and to an increase in employment -without any real changes in the net demand.

Information on wage bill and employment shares of private sector establishments comes from the PESA data set. Workers are divided into four different skill groups by age and education as follows: 1) less educated younger, 2) highly educated younger , 3) less educated older , 4) highly educated older. "Less educated" refers to people with basic, vocational and lower secondary education. "Highly educated" refers to people with educational qualifications from colleges, polytechnics or universities. "Younger" refers to 15-44-year old people and "older" to 45-64-year old people. Figures 1-3 presents clear evidence that the shares of older and highly educated people in population, in private sector employment and in aggregate private sector wage bill have steadily increased in 1988-1998. Evidently, among the different skill groups the share of "highly educated older" has increased most dramatically.

4.2 Decomposition Analysis

The observed aggregate changes in the skill mix of employment and the wage bill can reflect general changes in the skill mix of establishments' work forces within all establishments, a reallocation of employment between establishments with different skill structures or entering establishments with a different skill mix replacing exiting establishments with a different skill mix. In what follows we decompose the shifts in each skill group's (j) share in the aggregate wage bill and employment between (t-s) and (t), ΔS_j, into within-establishment changes, between-establishments changes and into entry and exit effects as

$$\Delta S_j = \sum_{i \subset C} \underbrace{\Delta S_{ji} \overline{P}_i}_{within} + \sum_{i \subset C} \underbrace{\Delta P_i \overline{S}_{ji}}_{between} + \underbrace{(S_{jt} - S_{jt}^C)}_{entry} + \underbrace{(S_{jt-s}^C - S_{jt-s})}_{exit}$$

for i=1,...,n establishments. $S_j = \frac{E_j}{E}$ is the share of skill group j in employment or the aggregate wage bill, and superscript C denotes continuing establishments, that is the establishments which appear in both the initial (t-s) and the end year (t). $P_i = \frac{E_i}{E}$ is the proportion of establishments i in total employment or wage bill and $S_{ji} = \frac{E_{ji}}{E_i}$ is the share of skill group j in employment (or the aggregate wage bill) at establishment i. A bar over a variable indicates the average of the variable over the initial and the end year. The first term on the right-hand side is the *within-effect*. It reports how much of the aggregate change in the share of skill group j in employment or the total wage bill, ΔS_j, is due to the changes in the skill mix that occur within establishments. The second term is the *between-effect*. It describes how much the aggregate change in the share of skill group j is due to the changes in the relative employment shares of establishments with a different skill structure (i.e. reallocation of the employment from low-skill to high-skill establishments). The third term describes the *entry-effect,* which reports the change in a group's share attributable to the entry of new establishments. The last component of the right-hand-side equation is the *exit-effect*, describing the change that is due to differences in the skill structure of surviving and exiting establishments.

Results of the decomposition analysis can shed light on a variety of competing hypotheses. It has been often argued (e.g. Berman et al., 1994) that the within-establishment changes support the hypothesis of skill-biased technological change. This argument rests on the idea that skill-biased technological change leads individual establishments to replace unskilled workers with skilled workers, which leads to within-establishments changes in the skill mix. Trade is assumed to lead to between-establishments changes in the skill mix: Trade is expected to generate a shift in product demand towards skill-intensive products, which causes an increase in employment in skill-intensive establishments. Finally, the entry can reflect both of these reasons: It has been argued that entry is a primary way in which a new technology is introduced into the economy, as entering establishments displace outmoded exiting plants (e.g. Dunne, et al, 1996, and Cabellero et al, 1994). On the other hand, demand shifts towards skill-intensive products have contributions to the entry of new establishments.

Table 1 reports the decomposition results for changes in the employment and wage bill shares of four different skill groups in Finnish private sector establishments from the PESA data set in 1988-2001[2]. The change is in absolute terms, meaning that the magnitude of the change also reflects the initial share of type j labour in establishments' work force. The results imply that the work force of the Finnish private sector establishments is becoming older and more educated. The increase in the share of highly educated older workers has mainly happened within establishments, while the increase in the share of younger highly educated workers is mostly due to the entry of new establishments and to the increase in employment of establishments which employ relatively more highly educated younger workers. The results provide evidence that new and enlarging establishments employ relatively more younger highly educated workers. The exit-effect for both less and highly educated older workers is negative, which implies that the exiting establishments hire more older workers than the surviving ones. The within-effect for highly educated younger workers is negative, implying that their share has diminished within establishments. The results for two subperiods, recession (1988-1994) and recovery (1995-2001), show clear evidence that the change in the skill structure of establishments happened mainly during the recession.

To interpret the results, it is essential to keep in mind that the increase in the share of older workers within plants might simply reflect the overall ageing of establishments' work force. That is, if a relatively large share of workers passes the 45-year-old mark, as the middle age cohorts are relatively

[2]It is worth emphasizing that the data set consists of all Finnish private sector establishments with more than two workers in the years 1988-2001, so that there should not be significantly artificial disappearences and appearences of plants in the data set (due to different sampling or changes in identification codes). This makes it possible to create reliable measures of plant entry and exit.

much bigger in Finland than the young ones (see figure 7), then the relative share of workers turning into "older workers" is much bigger than the share of workers that enter or exit the work life. The increase in the share of older workers within establishments might simply reflect the fact that during the recession few people were hired and the ones who were already employed were getting older. There is no reason, however, to reject the hypothesis that there might be changes in firms' hiring and firing decisions.[3].

5 Empirical Model

To examine empirically whether technological change is biased towards certain skill groups we relate the optimal skill composition of establishments' work forces into observable technology variables. The empirical counterpart of the equation (2) that describes the optimal skill mix in production is a model that describes the share of different labour inputs in labour demand. In order to derive the optimal labour demand equations we follow the approach taken in a number of previous studies (e.g. Bartel et al., 1987), where the long-run wage bill share equations are derived from the trans log cost function. The cost function is a function of total labour costs, rather than total costs of production. Ignoring raw materials is acceptable, if they are assumed to be separable from capital and labour. The only variable factors of production are the labour inputs, since capital and technology stocks are assumed to be quasi-fixed. To keep the model as simple as possible, the labour force is divided into four groups by their age and education. Taking the second order Taylor series expansion of the cost function (2) we obtain the trans log cost function

[3] i.e. Lilja (1996) provides evidence that during a recession the new hires in the Finnish manufacturing sector were on average more experienced and educated than in other periods. Piekkola and Böckermann (2000) find that the adjustments of labor demand during the recession were mainly carried out with younger workers (last in, first out).

$$\begin{aligned}
\ln C &= \beta_0 + \sum_{i=1}^{4} \beta_i \ln W_i + \beta_k \ln K + \beta_y \ln Y + \beta_t' \mathbf{T} + \\
&\sum_{i=1}^{4} \sum_{j=1}^{4} \delta_{ij} 1/2 \ln W_i \ln W_j + \sum_{i=1}^{4} \delta_{ik} \ln W_i \ln K + \\
&\sum_{i=1}^{4} \delta_{iy} \ln W_i \ln Y + \sum_{i=1}^{4} \delta_{it} \ln W_i' \mathbf{T}
\end{aligned} \tag{3}$$

Where $\mathbf{T}$ is a vector of variables describing the state of technology and K is capital. Differentiating by each skill groups wage W_j and using the Shephard's Lemma we obtain the labour cost share equations for each skill group j:

$$S_j^* = \frac{\partial \ln C}{\partial \ln W_j} = \beta_j + \sum_{i=1}^{4} \delta_{ji} \ln W_i + \delta_{jk} \ln K + \delta_{jy} \ln Y + \delta_{jt}' \mathbf{T} \tag{4}$$

where S_j^* is the long run optimal share of type j labour in total labour costs. The model implies that the skill structure of a firm's work force, given the level of output Y, depends on the prices of all labour inputs W_j, capital K and the "state of technology" $\mathbf{T}$, which is assumed to capture all the structural factors that affect the optimal skill mix within a given firm, that is, both the changes in product demand as well as technological change.

The main object in the study is to examine the impact of technological change and trade on the skill structure of labour demand. Hence, the primary variables of interest are the structural variables, $\mathbf{T}$, that are used to measure these phenomena. We use *R&D/sales ratio* as a variable that describes the "technology level" of firm. The main argument is that firms investing relatively more in R&D activities are more technologically advanced. The major explanation for this is that the nature of R&D work varies fundamentally from that of other forms of work -the tasks are non routine and there is a need for continuous learning. The R&D variable has also been widely used in literature to describe those firms or industries that have a high tech status (e.g. Berman, et al., 1994, Allen 2001). The obvious drawback of R&D intensity is that it is only an input, and it describes where the innovation is originated, not where it is used. That is, unlike computer investments, it does not directly measure the use of new technology in production process. However, there are a number of studies that provide evidence that R&D activities are clearly complementary to various other changes in firms' production technology, such as the adoption of new machinery in production, and that it does a reasonably good job of proxying the outputs of innovative processes[4].

As a measure of internationalization we use a plant's exports related to total shipments. This *export-share* is assumed to capture the changes in demand for final goods, and hence it is mainly assumed to affect the reallocation of employment *between* plants or industries. However, as argued by Bernard and Jensen (1997), the changes in product demand might represent switches from production of one good to another even at the plant level. Hence, export intensity might have an impact on both between- and within-establishments changes in labour demand.

Imposing homogeneity restrictions the stochastic counterpart of the wage bill share equation for skill group j is

$$\begin{aligned} S_{jit} &= \beta_{ji} + \delta_{j1} \ln(\frac{W_{1it}}{W_{4it}}) + \delta_{j2} \ln(\frac{W_{2it}}{W_{4it}}) + +\delta_{j3} \ln(\frac{W_{3it}}{W_{4it}}) \\ &\quad +\delta_{j5} \ln K_{it} + \delta_{j6} \ln Y_{it} + \delta'_{jt} \mathbf{T}_{it} + \epsilon_{jit} \end{aligned} \tag{5}$$

where j indicates the skill group, i the establishment, and t the time period, S_{jit} is the wage bill share of type j labour, W_{jit} is the wage for

[4]There are increasing number of studies which use alternative, and more direct measures of technology, such as "implementation of new automation technologies" (see e.g. Doms, Dunne, and Troske, 1997, Entorf and Kramarz, 1998 and Siegel, 1998).

skill group j, K_{it} is the capital, Y_{it} is the level of output (value added), $\mathbf{T}_{it}$ is a vector of technology and demand shift variables, and β_{ji} represents unobservable establishment specific time invariant effects. Vector $\mathbf{T}_{it}$ can be decomposed into observable technology or demand shift variables, and into time trend, which reflects common shifts in skill mix across establishments, as $\mathbf{T}_{it} = (export/sales_{it},\ R\&D/sales_{it},\ t)$. In our empirical analysis we replace time trend by a full set of year dummies. The primary focus of our estimations is on the impact of R&D-intensity and export share on the wage bill share of different skill groups. The output variable is included to capture possible non-homothecity. The coefficient of the capital stock variable is assumed to reflect complementarity of capital with certain skill groups. We would, hence, expect it to be positive for skilled (highly educated) workers. The dependent variable (wage bill share) is constructed as: $S_{jit} = W_{jit}E_{jit}/\sum_{j=1}^{4} W_{jit}E_{jit}$, where W_{jit} is the wage for the skill group j in establishment i at time t, E_{jit} is employment of skill group j in establishment i at time t.

As we are estimating the impact of the variables on the wage bill *share* of different skill groups, the estimated coefficients total zero, $\sum_{j=1}^{4} \delta_{jv} = 0$, for all variables v in the model. The above restrictions imply that row sums equal zero. The model provides a set of seemingly unrelated regression equations, where the error terms of different share equations are correlated. In order to capture the efficiency due to the correlation of disturbances, the system should be estimated jointly by generalized least squares as a standard SUR -model. However, each share equation can be estimated consistently, if not efficiently, by OLS (assuming the OLS assumptions hold). We estimate the model separately for each skill group[5].

There are a number of issues that must be addressed before estimating the model. First, there is the treatment of wage variables. As there is a direct

[5]For comparison the model was also estimated as a system of seemingly related regression equations (SUR) by feasible generalized least square. The system estimations of the model did not significantly increase the efficiency of the estimates.

relation between the explained variable (wage bill share) and the wages, there is no reason to believe that relative wages would not be correlated with unobservable factors that influence the group's share in the total wage bill. Hence, it is not plausible to treat relative wages as exogenous variables. Furthermore, the wage variation across establishments can be confused with variation in unobservable labour quality differences. In other words, there is assumed to be little useful exogenous variation in wages for the purpose of this type of analyses. Following the major part of the previous studies that use a similar framework (e.g. Berman et al., 1994, Dunne et al., 1996) we exclude the relative wage variables from the model and assume that the relative wage variation in time dimension is equal across all establishments, so that the time dummies capture the wage variation in time dimension[6]. Time invariant establishment-specific differences in relative wages are assumed to be captured in establishment-specific fixed effect.

Another issue is the endogeneity of technology variables. If R&D itself is chosen on the basis of economic incentives, it is unlikely to be independent of the factors that influence the firm's decision to employ workers from different skill groups. Hence, the unobservable factors that influence the skill structure of the establishment's work force are likely to be correlated with the R&D/sales-ratio and the estimated coefficient is likely to suffer from the endogeneity bias. However, as we were not able to come up with an appropriate instrument, the analysis is carried out by assuming exogeneity of explanatory variables. In the interpretation of the results one should keep in mind that the estimated impact of R&D does not necessarily represent a causal impact of this variable on the skill demand.

Finally, the overall ageing of the population complicates our analysis somewhat: As the middle-aged cohorts are relatively bigger than the entering ones, the share of over-45-year-old workers seems to be continuously

[6]The inclusion of relative wage variables did not change the results. See table 5 in appendix.

growing, even if there are no real changes in firms' employment (no hiring or firing). How are we able to control for changes in the skill mix that are due to within-plant ageing? If the increase in the share of older workers within a plant is mainly due to the ageing of the plant's current employees, the average share of older workers is expected to grow the same rate in all plants. Hence, we assume that the inclusion of the full set of time dummies will net out the effect of ageing and measure the impact of the variables on the changes in the skill mix apart from overall ageing.

6 Estimation Results

The model is estimated using two different samples: the linked LDPM-PESA sample covering years 1988-2001 and the R&D sample for 1991-2001. The table 2 shows the mean values of the main variables in the model. The labour force is disaggregated into four different skill groups by age and education as previously. The first three columns indicate that there is not a significant difference in the share of different skill groups between exporting and non exporting plants. The exporters seem, however, to pay higher wages, especially for highly educated workers. They are also bigger, more capital-intensive and more likely to have R&D activity. The next three columns show the descriptives for the R&D sample. Plants with R&D activity seem to be less likely to employ less educated younger workers, while there is no difference in the share of older less educated ones between R&D and non-R&D plants. Plants with some R&D activity employ also more highly educated workers in both age categories, pay higher wages (especially for highly educated workers), are bigger, more capital-intensive, and export more.

Table 3 reports the estimation results of the wage bill share equations for LDPM sample. Models (1) and (2) have the export share as the only additional "demand shift" variable. In addition the model controls for real capital stock, real value added and for fixed regional- and two-digit industry effects. The model includes a full set of time dummies to rule out the effects of common shifts in establishments' skill mix, such as ageing, and to control for over time variation in relative wages. Standard errors are reported in parentheses. The OLS estimation results of model (1) indicate that increase in the exports/shipments-ratio has a positive impact on the share of highly educated workers. The magnitude of the coefficient is bigger for younger highly educated workers. Model (2) controls for the establishment-specific fixed effects. The results show that allowing for establishment-specific fixed effects greatly reduces the explanatory power of the export-variable. The results indicate that increase in the relative level of exports does not have a significant effect on the changes on the skill mix within establishments. Contrary to the model without fixed effects, the results suggest that physical capital and younger workers are complements. The positive effect of the capital stock variable seems to be stronger for highly educated, younger workers. For both highly and less educated older workers the impact of capital appears to be negative. Thus, the findings indicate that the hypothesis of capital-skill (education) complementarity fails to hold for older workers.

Table 4 shows the estimation results for R&D sample for 1991-2001. The specification (1) includes export-intensity as the only demand shift variable. The model controls for region, industry and time-effects. The OLS estimation results of model (1) clearly show significant and positive impact of the export/shipments-ratio on the share of highly educated workers. The magnitude of the coefficient is bigger for younger highly educated workers. Specification (2) includes also R&D/sales-ratio as a "technology variable". The inclusion of R&D-variable decreases the coefficient on the export-share variable a bit, but it remains significant indicating that exports increase the demand for highly educated workers, especially for the younger highly educated ones. The result show significant and positive impact of the firm-level R&D/sales ratio on the share of highly educated workers and negative effect on the less educated workers. The magnitude of the coefficient is bigger for younger highly educated workers. Hence, with respect to technology variables, the pooled OLS regressions provide expected results: an increase in the R&D intensity significantly increases the demand for highly educated younger workers while the impact of this variable is much less pronounced for older highly educated ones.

However, this results does not hold if we control for plant-fixed effects in the model. Columns 3 and 4 in table 4 report the results for specification which allows plant-fixed effects. As before, the inclusion of plant fixed effects greatly reduces the explanatory power of selected technology and demand shift variables. In most cases the estimated coefficients on these variables seem to be statistically insignificant. Surprisingly, the last specification (4) provides some evidence that increase in the relative share of R&D expenditure increases the demand for less educated younger workers and decreases the demand for highly educated younger workers. The effect on the relative share of older workers is insignificant.

We carried out a significant number of robustness checking and tried different specifications of the model. Table 6 in appendix shows some of these results. The second column in the table shows the results for a specification with relative wage variables. We report only the results of the fixed effects model. The sample size is somewhat smaller since we include only the plants for which the information on relative wages for all skill groups could be found. The result indicate that inclusion of wages did not change the results significantly. It seems that neither export-share nor R&D-variable significantly influence the skill demand within establishments. In order to take into account the endogeneity problem of the explanatory variables also estimated the model using lagged values of all the explanatory variables instead the current ones. In addition we also estimated the model in first-difference form and used the lagged level of explanatory variables as instruments. These estimations did not yield significantly different results, and provided no evidence that the selected proxies for technological change and trade would significantly influence the within-plant changes in skill demand.

Why do we get so different results when controlling for plant-fixed effects? One explanation for this finding might be that, at the plant level, the correlation between technology use and skill structure is primarily due to the fact that plants with more skilled workers are more likely to adopt new technologies, invest in R&D and export. Thus, neither level of R&D nor exports itself influences the demand for skills within plants. Another reason for the "too low" and insignificant coefficients of the variables in estimations with fixed effects might be, that these variables are subject to measurement errors, which causes OLS to underestimate the true parameters and this bias may exacerbated when controlling for fixed effects (see Griliches and Hausman, 1986)[7].

In summary, our cross sectional results are consistent with the view of skill biased technological change and trade: the selected technology and trade indicators, R&D intensity and export-share, are correlated with higher share of highly educated workers. The impact of these variables is much less pronounced or even insignificant for older highly educated workers, which might indicate that these changes are likely to make worker's skills obsolete more quickly. However, when controlling for the unobservable time invariant differences between plants, the results show little correlation between the changes in plant-level R&D activity or exports-ratio, and the changes in workforce composition of the plant. Plants that increase their level of R&D activity or exports do not appear to increase their relative share of highly educated workers[8].

These results do not mean that R&D activity or exports would not have

[7]To explore this possibility the model was also estimated in long difference form. The argument is that when one assumes that measurement errors are stationary and uncorrelated and that the serial correlation is between true regression variables is declining, the errors of measurement will bias the long difference estimators less than they will bias first difference or within-estimators. The result, using the sample of continuing plants did not change the results significantly.

[8]Doms et al. (1997) got similar results with US plant-level data.

any effect on the aggregate skill structure in the economy. Huttunen (2002) using decomposition methods similar as in Bernard and Jensen (1997) provide evidence that the relative employment share of highly educated workers has increased due to the relative growth of the R&D plants and exporters in Finnish economy. There has not been significant differences in the skill mix changes that have occurred within plants between exporting and non-exporting plants, or between R&D-plants or non-R&D plants. She concludes that exports and R&D intensity had significant contributions to changes in skill mix of labour demand by influencing the changes that happen between-plants, but not necessarily to the within-plant changes. We should also bear in mind, that we might still use too crude measure of skill[9]. Vainiomäki (1999) using Finnish data for 1988-1994, found no effect of R&D activity or export intensity on the relative share of highly educated workers within plants. However, when disaggregating the educational categories further he finds that R&D intensity had a positive impact for the higher university and vocational groups, but a negative one for the lower university and basic groups. The regression results show that R&D intensity seems to contribute to "within-group" educational upgrading from lower university to higher university and from basic to vocational education.

7 Conclusions

This study has examined the changes in the skill structure of Finnish private sector establishments during 1988-2001 and the impact of observable technology and trade variables on the manufacturing sector establishments' skill mix. The findings suggest that at the aggregate level establishments' skill structure has changed towards older and more educated workers, closely reflecting the changes in the skill mix of the population. The decomposition

[9] There seems to be a rising recent literature which are examine the effect of technological change on more detailed workforce skill compositions. See Morrision and Siegel (2001), and Autor, Levy and Murmane (2003).

analysis reveals that the increase in the share of older workers has mainly occurred within establishments, while the increase in the share of the younger highly educated has occurred between establishments and by entry of new establishments. The pooled OLS estimation results indicate that the selected technology indicators, firm-level R&D intensity, and plant-level export share, increase the demand for highly educated workers, but the impact is much less pronounced for older highly educated ones. However, these results do not hold after controlling for time-invariant unobservable heterogeneity between plants. The fixed-effects OLS estimation results provide no evidence that increase in the level of R&D-activity or exports would affect the structure of the workforce within plants. With respect to capital-stock variable we find evidence that increase in the level of capital stock within plants increases the demand for younger workers in both educational categories, and decreases the demand for older workers respectively. In general, there seem to be significant differences in the sign and the magnitude of the coefficients within the same educational category. This suggests that the disaggregation of labour by educational level only might hide substantial heterogeneity within educational groups and, thus, provides support for our method to disaggregate labour by age as well.

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APPENDIX TO SECTION II

Figure 1. Unemployment rate in Finland in 1988-2001

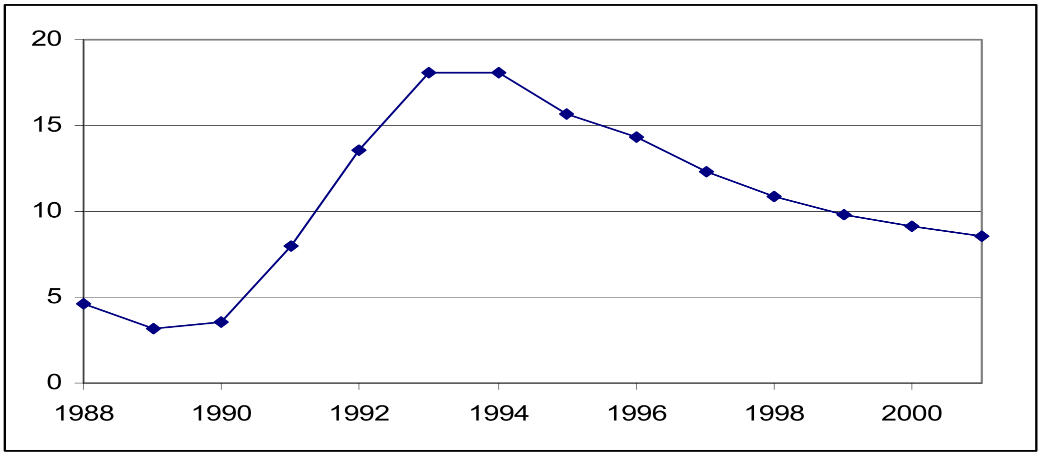

Figure 2. Export share in manufacturing in 1988-2001

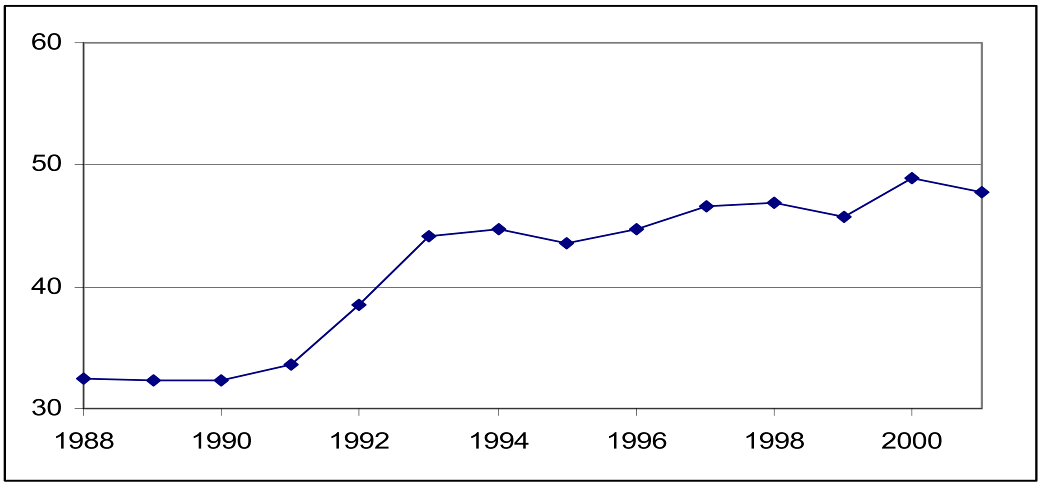

Figure 3. Share of total R&D expenditure

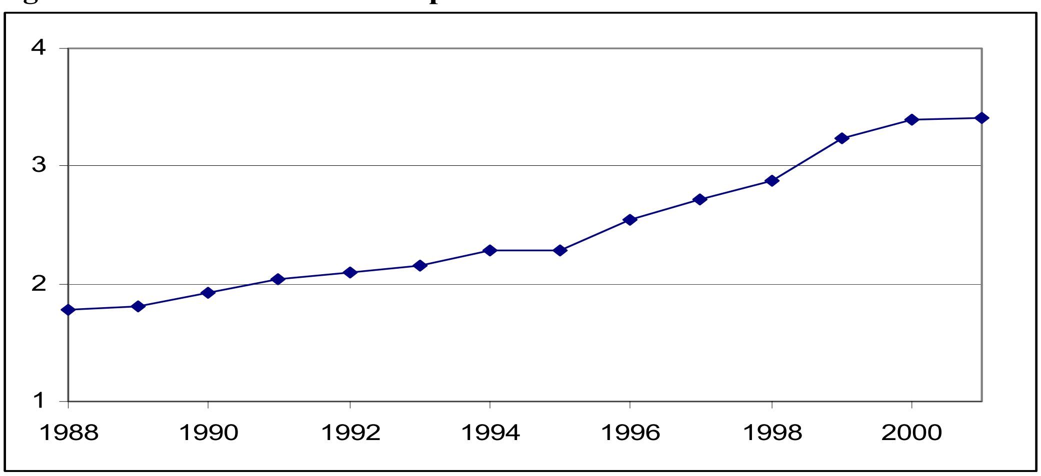

Figure 4. Population shares 1990-1998

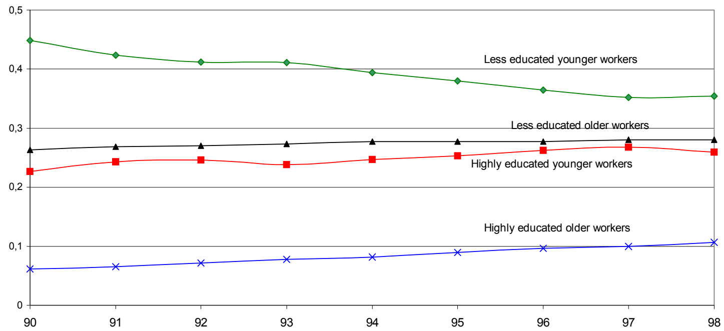

Figure 5. Employment shares 1988-1998

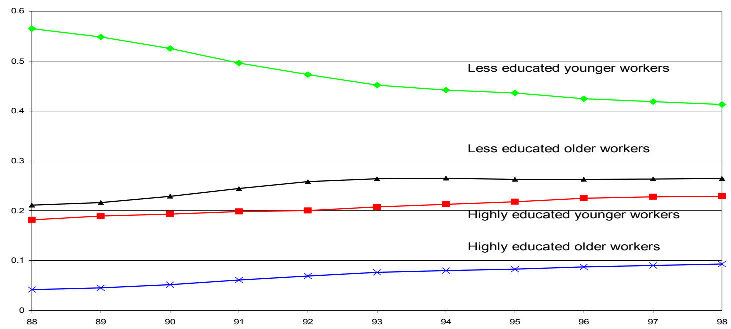

Figure 6. Wage bill shares 1988-1998

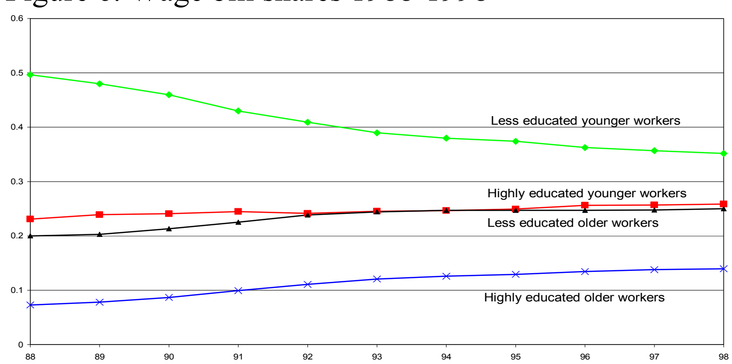

Figure 7. Age distribution of Finnish working age population in 1988 and 1998

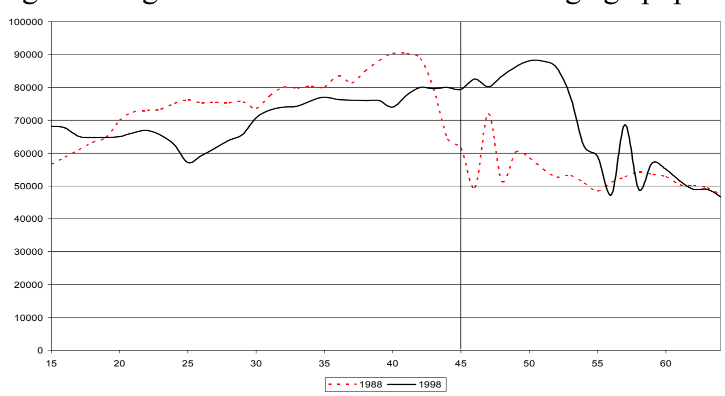

Table 1 Decomposition of the change in employment and wage bill shares of skill groups during 1988-2001

Period	Employment				Wage bill			
1988-2001	1	2	3	4	1	2	3	4
Total	-0.168	0.049	0.056	0.063	-0.172	0.046	0.039	0.086
Within	-0.181	-0.002	0.113	0.069	-0.165	-0.027	0.101	0.091
Betw.	0.001	0.024	-0.020	-0.005	-0.010	0.041	-0.026	-0.006
Entry	0.013	0.026	-0.038	-0.002	0.005	0.032	-0.036	-0.001
Exit	-0.002	0.001	0.000	0.002	-0.002	0.000	0.000	0.002
1988-1994								
Total	-0.123	0.031	0.054	0.038	-0.116	0.016	0.048	0.053
Within	-0.114	0.005	0.072	0.036	-0.103	-0.011	0.065	0.049
Betw.	-0.004	0.009	-0.005	0.000	-0.005	0.008	-0.004	0.001
Entry	0.002	0.013	-0.014	0.000	-0.001	0.015	-0.014	0.000
Exit	-0.007	0.004	0.001	0.002	-0.008	0.004	0.001	0.003
1995-2001								
Total	-0.040	0.013	0.004	0.022	-0.049	0.028	-0.009	0.030
Within	-0.061	-0.014	0.041	0.034	-0.059	-0.017	0.033	0.043
Betw.	0.011	0.017	-0.020	-0.008	0.001	0.034	-0.026	-0.009
Entry	0.008	0.014	-0.020	-0.002	0.005	0.017	-0.018	-0.003
Exit	0.002	-0.004	0.002	0.000	0.004	-0.006	0.003	-0.001

The skill groups are: 1. less educated younger workers, 2. highly educated younger workers, 3. less educated older workers, 4. highly educated older workers.

Table 2 Mean values of the main variables in the data sets

	LDPM sample						R&D sample					
	All plants		Exporting plants		Non-export. plants		All plants		R&D plants		Non-R&D plants	
Variable	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Size (n)	41095	91.28	26220	114.65	14875	50.09	30798	93.00	12479	142.18	18319	59.49
n1	41095	43.62	26220	54.42	14875	24.57	30798	42.05	12479	62.09	18319	28.41
n2	41095	15.01	26220	19.51	14875	7.09	30798	15.86	12479	25.51	18319	9.28
n3	41095	26.17	26220	32.62	14875	14.80	30798	27.72	12479	42.31	18319	17.77
n4	41095	6.48	26220	8.10	14875	3.64	30798	7.37	12479	12.27	18319	4.03
Emp. share1	40768	0.50	26064	0.50	14704	0.51	30638	0.47	12392	0.44	18246	0.50
Emp. share2	40768	0.15	26064	0.16	14704	0.14	30638	0.16	12392	0.18	18246	0.15
Emp. Share3	40768	0.28	26064	0.28	14704	0.29	30638	0.29	12392	0.29	18246	0.29
Emp. Share4	40768	0.06	26064	0.06	14704	0.06	30638	0.07	12392	0.09	18246	0.06
Wb.share1	40768	0.47	26064	0.46	14704	0.48	30638	0.44	12392	0.41	18246	0.46
Wb.share2	40768	0.17	26064	0.18	14704	0.15	30638	0.17	12392	0.19	18246	0.16
Wb.share3	40768	0.27	26064	0.27	14704	0.28	30638	0.28	12392	0.28	18246	0.29
Wb.share4	40768	0.09	26064	0.09	14704	0.09	30638	0.10	12392	0.28	18246	0.09
Log. wage	40768	9.26	26064	9.27	14704	9.24	30638	9.34	12392	0.28	18246	9.30
Log. wage1	40071	9.15	25767	9.16	14304	9.14	30065	9.23	12082	9.27	17983	9.20
Log. wage2	36870	9.41	24573	9.43	12297	9.37	28047	9.46	11413	9.51	16634	9.43
Log. wage3	38987	9.21	25124	9.22	13863	9.21	29381	9.29	11861	9.33	17520	9.27
Log. wage4	28987	9.70	20244	9.72	8743	9.66	23268	9.74	10236	9.78	13032	9.71
Log. capital	33344	7.56	21455	7.87	11889	7.01	24481	7.62	10446	8.23	14035	7.16
Log. Value added	37895	12.41	23741	12.71	14154	11.90	28613	12.47	11192	13.00	17421	12.13
R&D/sales	41095	0.01	26220	0.01	14875	0.00	30798	0.01	12479	0.02	18319	0.00
R&D-dummy	41095	0.34	26220	0.38	14875	0.26	30798	0.41	12479	1.00	18319	0.00
Export/shipments	38679	0.20	23804	0.33	14875	0.00	29134	0.22	11526	0.29	17608	0.17
Log. sales	38673	8.68	23804	9.06	14869	8.06	29128	8.76	11526	0.29	17606	8.41

nj refers to number of employees in skill group j in the plant. The skill groups are: 1. less educated younger workers, 2. highly educated younger workers, 3. less educated older workers, 4. highly educated older workers.

Table 3 Regressions: LDPM-sample

	Model 1 coeff.	s.e.	Model 2 coeff.	s. e.
Dependent variable: Wage bill share of young less educated workers				
Constant	0.509***	(0.056)	0.305***	(0.030)
Log. Capital	-0.006***	(0.001)	0.003***	(0.001)
Log. Value add.	-0.010***	(0.001)	0.015***	(0.001)
Export-share	-0.026***	(0.003)	-0.001	(0.003)
R-sq.	0.244		0.263	
Dependent variable: Wage bill share of young highly educated workers				
Constant	-0.037	(0.044)	0.117***	(0.024)
Log. Capital	-0.003***	(0.001)	0.005***	(0.001)
Log. Value add.	0.013***	(0.001)	-0.004***	(0.001)
Export-share	0.033***	(0.003)	0.002	(0.003)
R-sq.	0.196		0.012	
Dependent variable: Wage bill share of old less educated workers				
Constant	0.567***	(0.050)	0.456***	(0.027)
Log. Capital	0.005***	(0.001)	-0.007***	(0.001)
Log. Value add.	-0.009***	(0.001)	-0.005***	(0.001)
Export-share	-0.011***	(0.003)	-0.001	(0.003)
R-sq.	0.157		0.189	
Dependent variable: Wage bill share of old highly educated workers				
Constant	-0.039	(0.031)	0.123***	(0.019)
Log. Capital	0.004***	(0.000)	-0.002***	(0.001)
Log. Value add.	0.007***	(0.001)	-0.006***	(0.001)
Export-share	0.004**	(0.002)	0.000	(0.002)
R-sq.	0.226		0.119	
Time dummies	yes		yes	
Region dummies	yes		yes	
Industry Dummies	yes		no	
Plant fixed effects	no		yes	
Observations	30936		30936	

Standard errors are in parenthesis.

Table 4 Regressions: R&D -sample

	Model 1		Model 2		Model 3		Model 4	
	coeff.	s.e.	coeff.		coeff.	s.e.	coeff.	s. e.
Dependent variable: Wage bill share of young less educated workers								
Constant	0.620***	(0.077)	0.617***	(0.077)	0.262***	(0.038)	0.263***	(0.038)
Log. Capital	-0.004***	(0.001)	-0.004***	(0.001)	0.006***	(0.001)	0.006***	(0.001)
Log. Value add.	-0.011***	(0.001)	-0.011***	(0.001)	0.015***	(0.001)	0.015***	(0.001)
Export-share	-0.020***	(0.004)	-0.017***	(0.004)	-0.001	(0.003)	-0.001	(0.003)
R&D/sales			-0.236***	(0.031)			0.062***	(0.023)
Rsq.	0.200		0.202		0.168		0.169	
Dependent variable: Wage bill share of young highly educated workers								
Constant	-0.046	(0.061)	-0.043	(0.061)	0.158***	(0.031)	0.157***	(0.031)
Log. Capital	-0.005***	(0.001)	-0.005***	(0.001)	0.002**	(0.001)	0.002**	(0.001)
Log. Value add.	0.013***	(0.001)	0.013***	(0.001)	-0.005***	(0.001)	-0.005***	(0.001)
Exp-share	0.034***	(0.003)	0.029***	(0.003)	-0.002	(0.003)	-0.002	(0.003)
R&D/sales			0.356***	(0.025)			-0.043**	(0.018)
Rsq.	0.207		0.214		0.014		0.015	
Dependent variable: Wage bill share of old less educated workers								
Constant	0.440***	(0.072)	0.438***	(0.071)	0.424***	(0.035)	0.423***	(0.035)
Log. Capital	0.006***	(0.001)	0.006***	(0.001)	-0.006***	(0.001)	-0.006***	(0.001)
Log. Value add.	-0.009***	(0.001)	-0.009***	(0.001)	-0.005***	(0.001)	-0.005***	(0.001)
Exp-share	-0.018***	(0.003)	-0.016***	(0.003)	0.002	(0.003)	0.002	(0.003)
R&D/sales			-0.191***	(0.029)			-0.027	(0.021)
Rsq.	0.144		0.146		0.122		0.122	
Dependent variable: Wage bill share of old highly educated workers								
Constant	-0.013	(0.046)	-0.013	(0.046)	0.156***	(0.025)	0.157***	(0.025)
Log. Capital	0.004***	(0.000)	0.004***	(0.000)	-0.002**	(0.001)	-0.002**	(0.001)
Log. Value add.	0.007***	(0.001)	0.007***	(0.001)	-0.005***	(0.001)	-0.005***	(0.001)
Exp-share	0.005**	(0.002)	0.004*	(0.002)	0.001	(0.002)	0.001	(0.002)
R&D/sales			0.071***	(0.018)			0.008	(0.015)
Rsq.	0.219		0.219		0.0811		0.081	
Time dummies	yes		yes		yes		yes	
Region dummies	yes		yes		yes		yes	
Industry Dummies	yes		yes		no		no	
Plant fixed effects	no		no		yes		yes	
Observations	22859		22859		22859		22859	

Standard errors are in parenthesis.

Tables 5 Additional Regressions (R&D sample)

Young.less ed.	Model 1 coef	se	Model 2 coef	se
Log(w1/w4)			0.112***	(0.007)
Log(w2/w4)			-0.052***	(0.004)
Log(w3/w4)			-0.029***	(0.007)
Log. Capital	0.009***	(0.001)	0.009***	(0.001)
Log. Value add.	0.015***	(0.001)	0.015***	(0.001)
Export-share	-0.002	(0.002)	-0.002	(0.002)
R&D/sales	0.036	(0.019)	0.034	(0.019)
Rsq. (within)	0.262		0.288	
young.highly ed.				
log(w1/w4)			-0.059***	(0.005)
log(w2/w4)			0.100***	(0.003)
log(w3/w4)			-0.031****	(0.005)
Log. Capital	0.003***	(0.001)	0.002***	(0.001)
Log. Value add.	-0.004***	(0.001)	-0.003***	(0.001)
Export-share	-0.001	(0.001)	-0.001	(0.002)
R&D/sales	-0.021	(0.015)	-0.022	(0.015)
Rsq. (within)	0.028		0.106	
old less ed.				
log(w1/w4)			-0.036***	(0.006)
log(w2/w4)			-0.010***	(0.003)
log(w3/w4)			0.079***	(0.006)
Log. Capital	-0.008***	(0.001)	-0.008***	(0.001)
Log. Value add.	-0.004***	(0.001)	-0.004***	(0.001)
Export-share	0.001	(0.002)	0.001	(0.002)
R&D/sales	-0.021	(0.017)	-0.019	(0.017)
Rsq. (within)	0.188		0.209	
old highly ed.				
log(w1/w4)			-0.017***	(0.005)
log(w2/w4)			-0.037***	(0.003)
log(w3/w4)			-0.019***	(0.005)
Log. Capital	-0.004***	(0.001)	-0.004***	(0.001)
Log. Value add.	-0.007***	(0.001)	-0.007***	(0.001)
Export-share	0.003	(0.002)	0.002	(0.002)
R&D/sales	0.006	(0.014)	0.006	(0.013)
Rsq. (within)	0.134		0.229	
Time dummies	Yes		Yes	
Region dummies	Yes		Yes	
Industry dummies	No		No	
Plant fixed effects	Yes		Yes	
Observations.	16653		16653	

Standard errors are in parenthesis.

III The Effect of Foreign Acquisition on Wages and Skill Composition

Abstract

This paper examines the effect of foreign acquisition on wages and employment of different skill groups using panel data on Finnish establishments for the years 1988-2001. Exploiting the availability of rich set of pre-acquisition controls, we use various regression and propensity score matching methods, including difference-in-differences matching. The results indicate that foreign acquisition has a positive effect on wages. The magnitude of this effect increases with the level of schooling of the workers. The wage increase is not immediate, but happens within 1-3 years from the acquisition. The results with respect to employment effects are less clear. While regressions provide evidence that there is no effect on plant's skill mix, the matching results indicate that acquired plants reduce, although slightly and slowly, the share of highly educated workers in their employment.

1 Introduction

Several studies have found that there is a positive relationship between firm's ownership status and its performance. Foreign-owned firms are larger, more productive, more skill-intensive and pay higher wages (see e.g. Feliciano and Lipsey, 1999, Blonigen and Slaughter, 2001, Conyon, Girma, Thompson and Wright, 2002). Less sure is, however, in what direction the causal relationship between foreign ownership and the wages works. That is, foreign-owned firms may be exceptional because foreign firms acquire high wage skill-intensive firms, or because foreign acquisition has a positive effect on firm's wages and skill-intensity. In addition, the possible effect of foreign acquisition on wages might be different for workers from different skill groups.

This study examines the effect of foreign acquisition on employment and wages in Finland. The aim is, in particular, to examine whether there are significant differences on the effect of foreign acquisition on wages and employment of workers from different skill groups. Moreover, we aim to put significant effort to examine whether the relationship between foreign ownership and wages or employment is simply a correlation or whether foreign acquisition itself has an effect on the wages and on the skill mix of plant's work force.

We use plant-level panel data with matched information on worker characteristics from Finnish manufacturing for the years 1988-2001. During this period Finland experienced a high increase in the share of foreign-owned plants. This increase might partly reflect the global increase in foreign direct investments and acquisitions. In addition, the period is marked with two phenomena which might have influenced the increase of the foreign-owned firms in Finnish labour market. First, Finland experienced a very severe recession in early 1990's, where unemployment rate rose from 3 percent in 1990 to 17 percent in 1994. The recession was associated with a rapid restructuring of the economy. Second, Finland joined the European Union in 1995.

We aim to improve the previous literature in three ways: First, we use unique plant-level panel data with matched information on employee characteristics *by skill groups*. These data allow us to examine whether the effect of foreign acquisition on employment and wages varies by the educational level of the workers. In addition, the data allow us to control for rich set of pre-acquisition characteristics of the plants, including a large number of employee characteristics, and thus to study whether the change in the ownership might influence the changes in the average characteristics of plant's employees. We can thus disentangle the effect of foreign ownership on wages from the effect on the quality of the labour force.

Second, in addition to standard regression techniques we use various propensity score matching methods, including difference-in differences matching introduced in Heckman, Ichimura and Todd (1997). The central idea in the matching methods is to base the estimation on a very careful matching of cases and controls using a rich set of observable characteristics. This is a way to make sure we use a suitable comparison group and take into account all the possible observable factors that affect the selection of plants for acquisition by foreign firm.

Third, the changes in employment and wages that are caused by foreign acquisition might not happen instantly. It is well known that there are important costs in both hiring and firing of workers, and these costs might vary by the skill level of the workers. These adjustment costs mean that changes in labour demand or in average wages do not happen instantly. We take this into account and examine the effect of foreign acquisition on wages and employment in different periods after acquisition.

The results from both matching and regression indicate that foreign acquisition has a positive effect on wages of all skill groups in domestic plants. The wage increase is not immediate, but happens within 1-3 years from the acquisition. The magnitude of this effect increases with the level of schooling of the workers. The result of the employment effect are less clear. The regression analysis using the whole sample indicates that foreign acquisition does not have an effect on the share of highly educated workers in plant's workforce. However, the matching results indicate that acquired plants reduce, although slightly and slowly, the share of highly educated workers in their employment. Thus, it seems that foreign owners decrease the number of highly educated workers in their new plants. However, the highly educated workers who remain in acquired plants are paid clearly more than identical workers in domestically-owned plants.

The paper is organized as follows: Next section briefly describes the theoretical background for the analysis and reviews some previous empirical findings. Third section describes the statistical framework. Fourth section presents the data sets. Fifth section provides the results. The last section concludes the paper.

2 Background and Previous Literature

2.1 Theoretical background

The modern theory of multinational enterprises (MNEs), the so called *industrial organization* -approach to international trade, suggests that foreign-owned firms are different from domestically-owned firms simply because they *need* to be different. If foreign multinational enterprises are exactly identical to domestic firms, they will not find it profitable to enter the domestic market. Foreign firms presumably operates against disadvantages such as inferior knowledge of local markets and tastes and inferior connections with local politicians and financial institutions. In order to overcome these drawbacks, the foreign firm must possess some firm-specific advantages, such as superior technology, that overcome the inherent advantages of local firms[1].

If multinationals do indeed possess such assets, then we would expect

[1]See e.g. Caves, 1996, Markusen 1995, Aitken and Harrison, 1996, Bloningen and Slaughter, 2001 and Barrell and Nigel, 1997

foreign-ownership to affect wages in several different ways. First, these assets are assumed to raise the productivity of the firms. Assuming that workers can bargain over any surplus generated, higher productivity would be expected to generate a greater surplus and hence higher wage rates. Second, workers employed by the multinational enterprise acquire knowledge of the superior technology and can spread their knowledge to local firms by switching employers. Foreign-owned firms might pay higher wages in order to prevent workers from moving to local competitor and spillover this superior knowledge[2].

A firm-specific human capital accumulation model by Görg (2001) offers a third explanation for higher wages paid by foreign-owned firms. The knowledge-based assets that foreign-owned firms are assumed to have, require better trained workers. This implies that firm-specific training is more productive in foreign firms relative to domestic firms. As a result workers in foreign-owned firms are assumed to have steeper wage profiles than workers in domestic firms. Fourth, foreign-firms might have size and communication problems compared to domestic firms. Foreign firms might seek industrial relations peace with higher wages (see e.g. Conyon et al., 2002).

Perhaps the most plausible explanation for higher wages paid by foreign firms is that these firms employ higher quality workers than domestic-owned firms. Theoretical work on multinational enterprises and skill demand to date has been based largely upon general equilibrium trade models with endownment-driven comparative advantage. These models provide mixed results, variously suggesting that greater MNE activity can either raise or lower the skill mix[3]. It is well-established fact, however, that most of the foreign investments flows are between pairs of developed countries (e.g. Markusen, 1995). Theory does not provide a straight-forward answer to the question what is the effect foreign-ownership on the relative wages and on

[2] See Fosfure et al. 2001.

[3] see e.g. Markusen, 1995, Markusen and Venables, 1998, and Feenstra and Hanson, 1997.

the skill demand between countries of similar skill-mix. There are, however, indirect ways how multinational enterprises can influence the skill demand within a country, industry or a plant. Foreign firms entering an industry will accelerate the rate of technological progress. This, in turn, will increase the relative demand and wages for highly skilled workers in that industry[4]. One argument for the plant-level changes in relative wages and demand for skills, is that foreign acquisition is assumed to be associated with reorganization of existing capacity and introduction of new ideas (Markusen, 1995). The organizational change is expected to raise the demand for skilled labour, since skills raise the ability to handle new information, and thus, the skill level of workers tends to reduce the costs of decentralization[5].

2.2 Previous empirical evidence

There exits a growing body of literature, which examine empirically the relationship between foreign ownership and wages. Among the first ones is the study by Aitken et al. (1997), which examines the relationship between wages and foreign investments in Mexico, Venezuela and United States using data at industry-district-level. They found that a higher level of foreign ownership in an industry and location was associated with higher wages in all of these countries. Feliciano and Lipsey (1999) replicate the results of significant positive wage premium of foreign ownership for US using also industry-regional level data. Lipsey and Sjöholm (2001) use cross-section plant-level data from Indonesia manufacturing and find that foreign-owned firms pay higher wages even after controlling for plant characteristics, industry and location.

However, without establishment-level panel data it is impossible to examine, whether this finding is due to unobservable differences between foreign- and domestically-owned plants, or whether the ownership status itself influences wages. Foreign-owned establishments might pay higher wages than

[4]see Barrel and Pain, (1997), and Taylor and Driffiled, (2004).
[5]see Bresnahan, Brynjolfsson and Hitt, 2001

domestically-owned establishment simply because foreign firms took over high-wage local establishments. Lipsey and Sjöholm (2002) attempt to deal with the problem by using panel data on Indonesian establishments. They find strong increase in both white- and blue- collar wages after foreign takeovers. The regression results without establishment- fixed effects show that foreign-owned establishments paid 29 percent more for blue-collar workers and 43 percent more white- collar workers than domestically- owned establishment with similar characteristics. If plant fixed effects were introduced, and thus, the permanent establishment-specific unobserved heterogeneity controlled for, the remaining differentials are 10 per cent and 21 per cent.

Conyon et al. (2002) examine the productivity- and wage- effects of foreign acquisitions in the United Kingdom using establishment-level panel data for the period 1988-94. They use the foreign-ownership change (acquisition) to control for unobserved differences between plants. They find that firms which are acquired by foreign companies pay in average 3,4% higher wages than domestic firms. However, when productivity is added in the vector of control variables, the wage premium due to foreign-acquisition disappears.

Almeida (2003) use the effect of foreign acquisition on domestic firms' wages and skill composition using firm-level panel data with matched worker-information for Portugal for the period 1991-98. She finds that there exists an important selection effect as foreigners "cherry pick" the domestic firms that pay higher wages and employ more educated workers. Wages did however increase somewhat after the acquisition The increase was highest for highly educated workers (13%), compared to that for medium-and low educated ones (5% and 3% respectively). These values are again substantially smaller than the ones she got from cross section.

Girma (2003) investigate the effects of the foreign takeovers on domestic skilled and unskilled wages using establishment-level panel data for UK. He finds that skilled workers, on average, experience a post-acquisition increase in the wage rate following an acquisition by a US firm, while no such effect is found following acquisition by EU firms or other nationalities. For unskilled workers, there are positive post acquisition wage effects from takeovers by EU firms in the electronics industry and US firms in the food industry.

Very recent study by Martins (2004) examine the effect of foreign ownership on wages using matched worker-establishment panel data for Portugal from 1991-99. Using OLS, he finds that foreign firms pay higher wages, even when firm and worker controls are added. However, this results does not hold with different econometric methods. The difference-in-differences analysis, both regression and matching, provide evidence that workers in firms that were acquired by foreign investors experience lower wage growth than the ones who were employed in firms that did not change their ownership status.

Studies which examine the effect of foreign acquisition on relative demand for different skill groups are much less numerous and results less clear. Blonningen et Slaughter (2001) examine the impact of inward FDI flows and rising foreign-affiliate presence on US skill upgrading using four-digit industry-level data for manufacturing from 1977 to 1994. They results suggest zero or even negative correlation between increases in foreign-affiliate activity and skill upgrading in the United States during the period. Taylor and Driffield (2004) use similar framework with industry-level panel data to examine the role of foreign direct investment on wage inequality in UK. They find that FDI has significantly contributed to increase in the skilled wage bill share.

Interestingly, the studies that use establishment level-panel data seem to find either negative or zero effect of foreign ownership on demand for highly educated workers. Lipsey and Sjöholm (2002) examine the changes in employment after takeovers and find a decrease in number of white-collar workers and a strong increase in blue-collar workers. Almeida (2003) find no significant changes in the workforce's skill composition following a foreign acquisition for Portuguese establishments.

3 Statistical Framework

The goal in this study is to examine the effect of foreign acquisition on the employment and wages of different skill groups in the acquired plants. We borrow the terminology from program evaluation literature (see e.g. Heckman et al., 1999). We define foreign acquisition as the "treatment", D. $D = 1$ denotes the treatment state, plant was acquired by a foreign firm, and $D = 0$ denotes the non-treatment state, plant was not acquired by foreign firm. $Y(D)$ is the outcome associated with each state, e.g. wages and the employment share of different skill groups. Treatment group consist of plants that were acquired by foreign firm. Control group consist of plants that remained domestically-owned. We use various regression and matching methods to examine the effect of foreign acquisition on the outcomes.

3.1 Regression model

We begin by estimating the effect of foreign acquisition on post-acquisition outcome using a linear regression model. The regression model can be describe as

$$Y_{i,t} = \mathbf{X}_{i,t}\beta + \sum_{j=0}^{2} D_{i,t-j}\delta_{j+1} + \alpha_i + \zeta_t + \mu_{i,t} \tag{1}$$

where $Y_{i,t}$,is the variable that describes the outcome of the plant i in period t (e.g. log. wages or employment share of different skill groups), $\mathbf{X}_{i,t}$ is a vector of observable plant, industry and local labor market characteristics, and $D_{i,t-j}$ is dummy variables indicating plant's foreign ownership status at $t-j$, α_i is the plant-fixed effect, and ζ_t is the year dummy. The interpretation of the estimated coefficients on the foreign ownership status, δ_1 to δ_3, is the following. Since the model includes plant-fixed effects, we are using the within-plants variation only, and thus the coefficient on the ownership variable can be interpreted as the effect of foreign acquisition. The effect of acquisition that happened within one year from the observation date is captured by the variable $D_{i,t}$, the effect of acquisition that happened two years ago is captured by the variable $D_{i,t-1}$, and the effect of acquisition that happened three years ago is captured by the variable $D_{i,t-2}$. Thus the estimated regression model gives an estimate for the foreign acquisition on outcome immediately after acquisition, 1-2 years after acquisition, and 2-3 years after acquisition. This allows us to see whether the possible changes in wages and employment of acquired plants happen instantly or after some adjustment period.

3.2 Matching estimators

Next we estimate the effect of foreign acquisition on employment and wages using different propensity score matching methods. The central idea in matching methods is that the bias, which arises due to differences in the characteristics of treatment and control group, is reduced when the comparison of outcomes is performed using treated and control subjects who are as similar as possible on their observable characteristics. The key assumption is the conditional independence assumption. This assumption requires that conditional on observables characteristics, X, the treatment and non-treatment outcomes, $Y(1), Y(0)$, and the treatment status, D, are independent. The propensity score matching method (Rosenbaum and Rubin, 1983) proposes a way to summarize the vector of pre-treatment characteristics, X, into single-index variable. The propensity score is the conditional probability of receiving treatment given the pre-treatment variables

We begin by estimating the propensity score. In this study the propensity score is the conditional probability for a plant of being acquired by a foreign firm. The binary-choice model which describes the probability of foreign acquisition for plant i is of the form

$$D_{it} = \begin{cases} 1 & \text{if } \beta X_{it-1} + \zeta_t + \gamma_j + \eta_r + \varepsilon_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where D_{it} is a binary variable which defines plant's acquisition status at year t. $D = 1$, if a plant which was domestically-owned in year $t-1$ is foreign-owned at year t, and $D = 0$ if which was domestically-owned in year $t-1$ is not foreign-owned at year t. X_{it-1} is a vector of factors that affect plant's probability of being acquired by a foreign firm[6]. Since the acquisition happens between t and $t-1$ we use the characteristics from period $t-1$ as the pre-treatment variables. In order to control for unobservable common industry, region and time effects the model also includes full set of controls for fixed industry (γ_j), region (η_r), and time-effects (ζ_t).

The next step is to use the estimated propensity score in order to estimate the average effect of foreign acquisition[7]. The idea is to use the outcome of the non-treated observations (plants that remained domestically-owned) with similar propensity score to proxy, what would have happened to treated observations (acquired plants) in the non-treatment situation. The Average effect of Treatment on Treated (ATT) for all type of cross section -matching estimators can be written as

$$\widehat{ATT}(S) = \sum_{i \in T \cap S_P} \frac{1}{N^T} \left[Y(1)_i - \sum_{j \in C \cap S_P} {}_{ij}\omega_{ij} Y(0)_j \right] \tag{3}$$

where $Y(1)_i$ is the treatment outcome for unit (plant) i, $Y(0)_j$ is the non-treatment outcome for unit j (comparison group outcome), N_T is the number of units in treatment group, T, and C denotes the set of control units, S_P

[6]The sample consists only of plants which were domestic-owned in year t-1. Thus, the acquisition status is the same as ownership-status.

[7]This is after testing that the balancing property holds, i.e. whether observations with the same propensity score have the same distribution of observable characteristics independently of treatment status. We use algoritm silimar to Ichino and Becker (2003).

denotes the region of common support and ω_{ij} is the weight that is used to match control units with each treatment unit.

Matching methods rely crucially on the assumption that there are no unobservable factors which affects both the selection into treatment and the outcome. In order to control for the possible bias that is due to selection on unobservables we compute the average effect of treatment on treated using the difference-in-differences matching estimator (Heckman, Ichimura and Todd, 1997). The difference-in differences matching estimator compares the difference in the outcome before and after the treatment of treated units with the difference in the outcome of the non-treated units in the same period. This estimator allows for the existence of unobserved time-invariant factors that affect the selection. The assumption that is required for the consistency of the estimator is that conditional on observables the growth in the outcome for the non-treatment units is the same as the growth in the outcome for the treatment units would have been in the absence of the treatment. The formula for ATT can calculated as

$$\widehat{ATT}(S) = \sum_{i \in T} \frac{1}{N^T} \left[(Y(1)_{it} - Y(0)_{it-1}) - \sum_{j \in C} {}_{ij}\omega_{ij}(Y(0)_{jt} - Y(0)_{jt-1}) \right] \tag{4}$$

where t is the post acquisition time period and $t-1$ is the pre-acquisition time period.

In both the cross section and difference-in-differences matching we use two different methods to match the treatment and control group observations. These methods differ in the weights, ω_{ij},they attach to members of the comparison group. The nearest neighbor matching method finds for each treated unit, T, the control unit, C, which propensity score is nearest. The matching is done with replacement, i.e. the same nearest control unit can be used many times (to be matched with several treatment units). The Kernel matching estimator matches every treated unit with a weighted average of all control units with weights that are inversely proportional to the distance between treated and control units[8].

4 Data

4.1 Description of the data sources

The main data source in this study is the Plant Level Employment Statistics Data on Average Characteristics (PESA). It is a longitudinal data on Finnish establishments, with linked information on worker characteristics aggregated on the establishment level by skill groups. The linked worker characteristics-establishment data are constructed by linking data on workers in the Employment Statistics database of Statistics Finland to data on plants of Business Registers and Industrial Statistics. The data set covers all the private sector establishments (except traffic and construction) with more than two workers. The time period is 1988-2001. The number of establishments is around 50 000 each year. Employees are aggregated into 70 different skill groups by education, age and sex. The data contains information on aggregate worker characteristics for each skill group, such as number of people, average monthly wage, general working experience, tenure and education. The data set does not have any specific information on establishment characteristics. However, each enterprise and its plant, has a unique identification code, which can be used to match additional information from other statistics and registers on the linked worker-plant database.

Another major data source used in the analysis is the Longitudinal Data on Plants in Manufacturing (LDPM), which is constructed especially for research purposes from Annual Industry Statistics. For the period 1974-1994 it covers all manufacturing sector plants with more than 5 workers and for the

[8]Kernel matching defines the weight as $\omega_{ij} = \frac{G(\frac{p_j - p_i}{h_n})}{\sum_{k \in C} G(\frac{p_k - p_i}{h_n})}$, where $G(.)$ is a kernel function and h_n is a bandwidth parameter.

period 1995-2001 it covers the plants of firms employing at least 20 persons. The number of plants varies between 9000 and 3000 each year.

For the purpose of our analysis we form data set by linking the PESA data set with LDPM data. The linked data set covers manufacturing plants from the years 1988-2001. As the LDPM data set for the years 1995-2001 consists only the plants of firms that employ at least 20 persons, the number of observations per year is considerably smaller after 1994. In order to have consistent data set we thus restrict the sample to cover only plants of the firms which employ at least 20 workers. This sample consists 46 290 plant-year observations.

The variables describing the employee characteristics are obtained from the PESA data set. All this variables are skill-group averages in the establishment. The main variables describing employee characteristics are: monthly wage, employment, wage bill share, tenure, age, and education. Employment describes the number of workers in a skill group working in an establishment during the last week of the year. The average monthly wage is calculated as the skill group average of the average monthly wages of individual workers who were employed in the establishment during the last week of the year. The average monthly wage for each individual employed is calculated by dividing the wage income by months of employment. The monthly wage bill for each skill group is formed by multiplying the average monthly wage of the skill group by the number of workers in the skill group employed in the establishment during the last week of the year. Age is the average age of workers in the skill group employed in the establishment during the last week of the year. Average education is calculated as the average of the years of schooling for each skill group, and average tenure is calculated as the average of the months of tenure in the skill group.

Variables describing the plant characteristics, including the foreign ownership status, are from the LDPM data set. The variable defining foreign ownership status is created using the information on the share of foreign owners of the plant. An establishment is labeled as foreign-owned if the share of foreign ownership is at least 20%[9]. The other main establishment characteristics used in the analysis are sales, real value added, real capital stock and exports.

We use two different samples in this analysis. In the basic regressions (described in section 3.1.) we use all the observations from the matched PESA-LDPM data for which we have information on the characteristics needed in regressions. These include the information on plant's foreign ownership status in the current year, and in the two previous observation years. This sample consists of plants from the years 1990-2001. In the matching analysis we use different sample. The construction of this sample is described below.

4.2 Matching Sample Construction

The sample of plants that was used in the matching analysis in this article is constructed as follows. From the overall data base, we first identify plants, which we can observe in the data set at least two consecutive years before the current year, and which were domestically-owned in those years. We label the current year as the period 1. The previous years are labeled as 0 and -1, and the following years 2 and 3. We divide these plants into treatment and control groups. The treatment group is the plants which were acquired by foreign firms in the period between 0 and 1. The comparison group is the plants which remained domestically-owned until the period 3. We remove from the sample all the plants that do not have information on all the observational characteristics that are used in matching and regressions. Since in matching we are using information from two years before the acquisition, and examine the outcome until the third year after acquisition, we can use

[9] We have two main reasons to us the 20 % threshold. First, Most of the previous studies label establishment as foreign-owned if 10 % or 20% of its ownership is foreign (e.g. Bloningen and Slaughter, 2001, Aitken Harrisen and Lipsey, 1995, Almeida, 2003). Second, most (88 %.) of the plants in our data with at least 20 % foreign ownership have more than 50% foreign ownership. We use 50% threshold for robustness checking.

only information on plants that we can observe for at least five consecutive years. The final matching sample consists of 14 762 observations. It covers the years 1990-1999. The number of foreign-acquired plants is 355. The number of observations in control group is 14 407 .

5 Results

5.1 Aggregate Trends in Finland during 1988-2001

The period from 1988 to 2001 was marked with several exceptional phenomena in Finland. During the early 1990 Finland experienced several adverse economic shocks, including the end of eastern trade induced by the collapse of Soviet Union, which partly led to exceptionally severe recession in early 1990's. The recession hit all the industries and regions and affected workers in all skill groups. The total unemployment rate rose rapidly from 3 % to 17% within three years. The period was also marked by a significant changes in the production structure. The recovery period was marked by a growth of new industries: namely of export oriented high-tech manufacturing sector. In the beginning of 1995 Finland joined the European Union. The foreign direct investments to Finland increased significantly during the whole period. Most of these investments were from other EU countries (see figure 1).

5.2 Descriptive Evidence

The results are reported in appendix. Table 1 reports the share of foreign-owned plants in the LDPM/PESA in 1989-2001 and the share of workers employed in foreign-owned plants in the data set. The share of foreign-owned plants has increased significantly during the period in Finland. While in the late 1980's only around 4% of plants were foreign-owned, in 2001 the share is 19%. Table 1 also shows how much of this increase is due to takeovers of domestic plants by foreign firms (acquisitions), and how much due to new plants started-up by foreign firms. Most of the increase in the number of foreign-owned plants is due to acquisitions. Table 2 shows that the increase in the share in the employment of foreign-owned plants has been even more rapid than the increase in the number of plants, from 5 to 22%. Acquisitions contribute for most of the increase.

Before presenting the matching and regression results it is interesting to see whether there are significant differences between wages and other observable characteristics of foreign-owned and domestically-owned plants in Finnish manufacturing. Table 3 reports the mean values of the main characteristics for the foreign-owned and domestically-owned plants in the sample. The results imply that foreign-owned plants pay higher wages for both highly and less educated workers than domestically-owned plants[10]. But they also have other observable characteristics which can explain higher wages: they are bigger, older, employ more skilled workers, are more likely to export, or to have R&D activity. The average employee characteristics of these plants vary as well. Foreign-owned plants employ workers who are older, have more years of schooling, and who have a longer tenure.

Evidently, this does not tell us whether the foreign-owned plants were different from the domestic-owned plants already before the acquisition happened. Table 4 describes the differences in the observable characteristics of acquired and non-acquired plants from the pre-and post-acquisition periods. The sample consists of plants for which we can find information on observable characteristics 2 years before the possible acquisition and 3 years after the acquisition. The pre-acquisition periods are marked as -1,0, and post-acquisition periods, 1,2, and 3. The acquisition happens between 0 and 1. The result shows that the plants which were acquired by foreign firms had characteristics which are associated with higher wages even before the acquisition happened. They are bigger, have higher sales, they have larger share of

[10]"Less educated" refers to people with basic, vocational and lower secondary education. "Highly educated" refers to people with educational qualifications from colleges, polytechnics or universities.

exports from they total sales, they employ workers that are older, have more schooling and longer tenure. In addition they employ less females and are more capital-intensive and productive. The difference in the characteristics remains after acquisition.

Next rows in table 4 report the differences in the four different outcome measures from the two periods preceding acquisition until the third year after acquisition. The outcome measures are: 1) logarithm of average wage of less educated workers in the plant, 2) logarithm of average wage of highly educated workers in the plant, 3) share of highly educated workers in employment, and 4) share of highly educated workers in total wage bill. The result show that foreign acquired plants pay higher wages for both highly and less educated workers even before the acquisition occurs. The difference in the wages increases after acquisition and continues increasing until second year after acquisition for less educated workers, and until third year after acquisition for highly educated workers. The acquired plants also employ more highly educated workers before they become foreign owned. The difference remains after acquisition, but diminishes in time.

5.3 Regression results for the whole sample

As shown in table 3, foreign-owned plants in Finland pay higher wages than domestically-owned plants, but also have other characteristics that are related to higher wages. We now ask whether foreign-owned plants pay higher wages given these characteristics, industry, and location. We begin our analysis by running an OLS regression on wages of different skill groups. Results are reported in table 5. The first column (model 1) is an OLS specification, where we control for various plant-, and worker-characteristics[11]. In addition the specification includes controls for common time-, region-, and two-digit-industry- effects. Consistently with previous studies, the pooled OLS result show that foreign-owned plants pay higher wages even after controlling for

[11] The worker characteristics are skill-group averages at plant level.

the plant-, and worker-characteristics, and for industry, region and common time effects. The foreign wage premium is higher for highly educated workers than for less educated workers: 0,054 and 0,032 respectively.

Regression analysis with rich set of controls for plant- and worker- characteristics within regions and within industries is likely to eliminate some of the bias that arises from the result of the possible selection of high-wage establishments for acquisition by foreign-firms. However, one possible source of bias remains. That is that there may be some unmeasured characteristics that are associated with both high wages and foreign ownership. In order to control for these characteristics model 2 includes plant-specific fixed effects. If plant fixed-effects are introduced the remaining foreign-ownership wage premium is reduced to 0,011 for less educated workers and to 0,014 for highly educated workers.

The last columns in table 5 (model 3) report the results for a specification which includes plant fixed-effects and foreign ownership dummies for current period, and for two previous periods. This means that plant's foreign-ownership status is allowed to affect wages in the current year, and also in the two years after the change in ownership (acquisition) has happened. The results indicate that the effect of foreign ownership grows in time. For less educated workers the effect of foreign ownership is strongest in the second year after acquisition, and for the highly educated workers on the third year.

Table 6 reports the results of the effect of foreign ownership on the share of highly educated workers in plant's employment and total wage bill. The results of the different specification, with or without plant fixed effects, indicate that foreign-owned plants do not employ more highly educated workers, once we take into account various plant-, and workers-characteristics, and the fixed location-, industry- and time-effects that might affect the skill demand.

5.4 Matching and regression results for the matching sample

The next important issue is whether the effect of foreign acquisition is heterogeneous with respect to observational characteristics. If this is the case, we must make sure a suitable comparison group exits. One way to address this problem is to use propensity score matching methods. The crucial requirement in matching is, that we take into account all the possible observational characteristics that might affect both the probability of being acquired by foreign firm and the outcome. In order to ensure this we will use rich set of worker, plant and region characteristics from different pre-acquisition periods. Since we want to examine how the effect of foreign acquisition evaluates in time we need to have information of the outcome variables from 3 post-acquisition periods. These requirements mean that the sample that can be used in matching is considerable smaller, as described in section 4.2. In this section we report the regression and matching results for this matching sample.

The propensity score, the conditional probability of being acquired by foreign firm, is estimated by parametric probit model. The results of the probit estimations are presented in table 7. The dependent variable gets value one if the plant was acquired by foreign firm between periods 0 and 1. The variables which are use to predict the probability of being acquired by a foreign firm, i.e. pre-treatment variables, are from the pre-acquisition periods 0 and -1. The pre-acquisition characteristics from period 0 include plant size (number of employees), squared plant size, logarithm of total sales of the plant, export/sales ratio and its square, share of exporting plants in two-digit industry, and share of foreign-owned plants in the two-digit industry, and total sales in the region (to control for the size of the market). The information from plant average characteristics are from period -1. These include the average years of schooling of plant's employees, average age of plant's employees, average tenure of plant's employees and the square of average tenure[12]. In addition the specification includes two-digit region controls, one-digit industry controls and full set of time dummies.

The estimation results indicate that plant size has a negative effect on the probability of being acquired by a foreign firm, once plant's total sales in the period are taken into account. Plant's sales have a significant positive impact on the acquisition probability. If the sales variable is excluded from the regression the plant size variable gets highly positive and significant coefficient. Plant's export/sales ratio is positively related to the acquisition probability. However, the share of exporting plants in an industry is negatively related to acquisition probability once plant's own exports are taken into account. This might indicate that these industries have higher transport costs, and firms are more likely to acquire plants directly from these industries rather than decide to trade. The share of foreign-owned plants in industry predicts positively the likelihood of being acquired. This is expected, since this variable might capture many unobservable industry-specific factors that lead foreign firms to acquire plants from these industries. The variable describing sales in the region, i.e. market size, gets positive but insignificant coefficient. Next we look at the effect of plant's average employee characteristics on the acquisition probability. Plants that pay high wages in period -1 are more likely to end up being foreign owned between 0 and 1. Also plants with highly educated and high tenure workers seem to be more attractive for foreign firms. Workers' average age decreases the probability of foreign acquisition.

Next we estimate the effect of foreign acquisition using the estimated propensity score. We begin by estimating the effect of foreign acquisition on average wages of less educated workers in a plant. The first rows in table 8 show the effect of acquisition on the average wages of the less educated workers in a plant in the period just following the acquisition, t =1. The first columns show the results from cross-section matching. That is, the

[12] _0 in end of the variable refers to period just before acquisition (0), and _1 to period 1-2 years before acquisition (-1).

dependent variable is the level of the wages in different post-acquisition time periods. As a benchmark we report a results from a regression in the first column, where the outcome variable is regressed on all the X's that are used to estimate the propensity score, and on a dummy which explains whether the plant is foreign-owned or not. Since the sample only includes the plants that are domestically-owned or were acquired by foreign firm during the period, this dummy can also be interpreted as an effect of foreign acquisition. We impose the common support condition, i.e. include only the observations, which have the propensity score within the common support region. The estimated coefficient on foreign-acquisition is again negative -0.009 and not significantly different from zero.

The next two columns present the estimated effects of foreign acquisition on average wages using different matching estimators. The nearest-neighbor estimator with replacement gives slightly stronger negative effect (-0.028), but it is still not statistically significantly different from zero. Next column reports the results from Kernel matching. While nearest neighbor matching uses only those control group observations that are closest to treated units, Kernel matching uses all the control group observations, but weights each observation according to its distance from the treated unit. Kernel matching estimator shows strong positive effect (0.060)[13].

The last three columns report the results from difference-in-differences regression- and matching estimations. The dependent variable is the difference of the wages between the pre-acquisition period (0) and the different post-acquisition time periods (1 in the first row). The fourth column shows

[13] We use here Gaussian kernel and the bandwidth 0.06. We also tried other bandwidths, such as 0.01 and 0.02. With smaller bandwidth choices the kernel estimates became smaller and less significant and thus, more closer to the nearest neighbour estimates. This makes sense, since the smaller the bandwidth choice, more weight is put on the control group observations which have propensity score that is closest to the treated units. The fact that the bandwidth choice makes a difference might indicate that the cross-section matching assumptions do not hold. The bandwidth choice did not have significant effect to the difference-in-differences matching estimator.

the result from regression, where the change in the logarithm of monthly wages of less educated workers from 0 to 1 is regressed on foreign-ownership dummy and on all the controls that were used to estimate the propensity score. The next columns report the results from nearest-neigbour and kernel difference-in-differences matching. The results again provide evidence that foreign acquisition does not have any significant effect on average wages of less educated workers. The estimated effect varies from 0.006-0.008. There seems to be much less differences between regression, kernel and nearest neighbor estimates than with cross-section matching estimators. This indicates that the cross-section matching assumptions (conditional independence assumption) might not hold for our sample, and once the permanent differences between the plants are taken into account by difference-in-differences matching or regression, the result seem to be more robust.

These result do not necessary mean that acquisition does not have any effect on wages of less educated workers. The changes in employment and wages that are caused by foreign acquisition might not happen instantaneously. Next rows in table 8 report the results on the effect on the wages of less educated workers in the second year following the acquisition. The cross-section matching results are still quite unrobust, although clearly more positive than in the first year. The difference-in-differences matching and regression indicate that the foreign acquisition has a positive and highly significant effect on the wages of highly educated workers in the second year after acquisition. The magnitude of the effect varies between 0,029-0,030. When looking at the wages at the third year after acquisition the result remain robust. Less educated workers in plants which were acquired by foreign firms earn significantly more in the third year after acquisition than workers in plants that remained domestic during that time. The difference in the wages has, however, decreased a bit from the previous year.

Table 9 reports the results of the effect of foreign acquisition for highly educated workers. Now both the matching and regression indicate positive, although mostly not significant effect on the wages already at the year immediately after acquisition. The effect vary from 0,013 to 0,036. As in previous table, the difference-in differences results are more robust to different estimation methods. In the second year, this effect is clearly stronger, varying from 0.019 to 0.046 and often statistically significant. The results for the third year indicate more robust results. The effect of foreign acquisition on wages of highly educated workers in the third year after acquisition is between 0.026-0.056. The difference-in-differences models indicate highly significant and robust effect that varies between 0,031-0,035. Thus, it seems that acquisition raises the wages of highly educated workers, but this raise is not immediate.

Table 10 shows the results of the effect of the acquisition on the share of highly educated workers in plant's employment. The result indicate that foreign acquisition does not have any effect on the skill composition of plant's workforce in the first two years after acquisition. In the third year, the difference-in-differences results indicate significant and negative effect of the foreign acquisition. Table 11 replicates the results using the share of highly educated workers in total wage bill as the outcome variable. The result indicate again no significant effect on the first two years, but negative effect on the third year. The magnitude of the effect is slightly lower than for the employment share, which might indicate that the relative increase in high skilled wages compensates the drop in total employment share.

Finally we look whether there is even more heterogeneity in wage effects according to the educational level of workers. Table 12 reports the difference-in-differences matching results for the effect of foreign acquisition on wages of four different educational categories: basic, vocational, lower university, and higher university. The results again indicate that the magnitude of the effect depends on worker's educational level. There is a clear increase in the magnitude of the effect by the level of schooling of the workers.

All in all, the result indicate that there is a clear positive effect of foreign acquisition on the wages, but this raise in wages is not immediate. The effects seems to be stronger, and more long-lasting for highly educated workers. This might not indicate that acquisition increases demand for skills, since the acquired plants are decreasing the share of highly educated workers in their workforce. The decrease in the employment share is however very modest.

6 Conclusions

This paper examines the effect of foreign acquisition on wages and employment of different skill groups using panel data on Finnish establishments for the years 1988-2001. Exploiting the availability of rich set of pre-acquisition controls, we use various regression and propensity score matching methods, including difference-in-differences matching.

Both regression and matching results indicate that foreign acquisition has a positive effect on wages. The magnitude of this effect increases with the level of schooling of the workers. Moreover, the wage increase is not immediate, but happens within 1-3 years from the acquisition. This can be due to various reasons. First, part of the foreign wage premium might be explained by the fact that foreign-firms do more on-the-job-training, and thus the wage growth in foreign-owned firms is higher. This indicates that wages in plants that are acquired by foreign-owned firms do not raise immediately, but within some years after acquisition. The finding that wages seem to rise more rapidly for highly educated workers might indicate bigger returns to training for highly educated workers[14]. Second reason for the fact that wages do not rise immediately, is that acquisition can involve organizational changes within plant, and the implementation of new work practises might take time. Third, the changes in average wages can be associated with changes of employment composition of plant's workforce. Since there are adjustment costs associated with these employment changes, they are not likely to be immediate. Finally,

[14]See e.g. see Altonji and Spletzer (1991).

due to possible measurement problems, the exact timing of the acquisition might be uncertain.

The result on employment effect are less clear. The regression analysis using the whole sample indicates that foreign acquisition does not have any effect on the share of highly educated workers in plant's workforce. However, the matching results indicate that acquired plants reduce, although slightly and slowly, the share of highly educated workers in their employment. This finding, although quite surprising, is in line with findings from the few earlier studies that have examined the changed in skill mix after acquisition (Lipsey and Sjöholm (2002), Almeida (2003)). It seems that foreign owners decrease the number of highly educated workers in their new plants, but the highly educated workers who remain are paid clearly more than identical workers in domestically-owned plants. The fact that these changes do not show before the third period after acquisition might indicate that there are important adjustment costs related to hiring and firing of workers.

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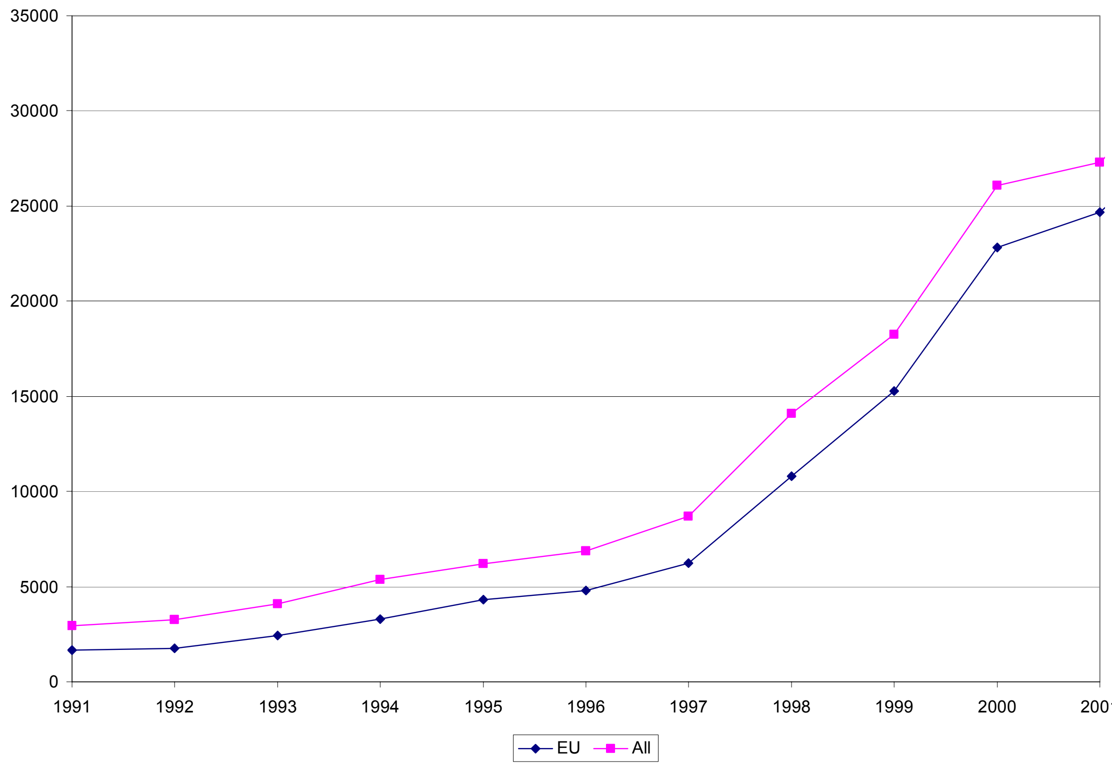
APPENDIX TO SECTION III

Figure 1 Foreign direct investment in Finland in 1991-2001, stock of investment at the end of the year, EUR million



Source: Bank of Finland

Table 1 Number and share of foreign-owned plants in the sample of Finnish manufacturing plants in 1989-2001

	All plants	Foreign-owned plants							
	All	All foreign owned		Foreign owned at t-1		New plants		Acquired plants	
Year		Freq.	%	Freq.	%	Freq.	%	Freq.	%
1989	3775	154	4.08	114	3.02	32	0.85	8	0.21
1990	3941	173	4.39	126	3.20	27	0.69	20	0.51
1991	3758	174	4.63	138	3.67	23	0.61	13	0.35
1992	3390	148	4.37	120	3.54	13	0.38	15	0.44
1993	3263	290	8.89	116	3.56	52	1.59	122	3.74
1994	3364	323	9.60	246	7.31	33	0.98	44	1.31
1995	2951	294	9.96	261	8.84	20	0.68	13	0.44
1996	2994	298	9.95	261	8.72	18	0.60	19	0.63
1997	2966	410	13.82	261	8.80	23	0.78	126	4.25
1998	3036	467	15.38	298	9.82	47	1.55	122	4.02
1999	3000	492	16.40	342	11.40	29	0.97	121	4.03
2000	3016	469	15.55	395	13.10	47	1.56	27	0.90
2001	3028	585	19.32	412	13.61	65	2.15	108	3.57

Table 2 Employment in foreign-owned plants in the sample of Finnish manufacturing plants in 1989-2001

	All plants	Foreign-owned plants							
	All	All foreign owned		Foreign owned at t-1		New plants		Acquired plants	
Year		Freq.	%	Freq.	%	Freq.	%	Freq.	%
1989	299516	14020	4.68	10398	3.47	3400	1.14	222	0.07
1990	313516	17708	5.65	12456	3.97	1492	0.48	3757	1.20
1991	274683	13823	5.03	11533	4.20	599	0.22	1691	0.62
1992	255073	10597	4.15	8631	3.38	577	0.23	1389	0.54
1993	244972	14982	6.12	9156	3.74	1347	0.55	4476	1.83
1994	257383	19720	7.66	14527	5.64	1524	0.59	3669	1.43
1995	253064	19818	7.83	17783	7.03	554	0.22	1481	0.59
1996	255878	21063	8.23	16907	6.61	1036	0.40	3120	1.22
1997	269185	43647	16.21	21006	7.80	994	0.37	21647	8.04
1998	275450	40728	14.79	27556	10.00	2051	0.74	11118	4.04
1999	257901	49861	19.33	32097	12.45	1496	0.58	16268	6.31
2000	263745	50370	19.10	44338	16.81	2068	0.78	3964	1.50
2001	259915	58954	22.68	47848	18.41	3377	1.30	7729	2.97

Table 3 Descriptive Statistics for the sample

	Domestic-owned		Foreign-owned	
Variable	Obs	Mean	Obs	Mean
Plant size	35017	90.51	3337	100.40
Plant age	19019	8.74	1986	9.12
Wage	34730	11821	3312	13406
Wage less ed.	33349	10822	3107	11882
Wage highly ed.	16112	16363	2014	17951
Wage bll	35017	1145986	3337	1349801
Av. Schooling	34730	11.54	3312	11.77
Av. Tenure	34730	10.53	3312	11.63
Av. Age of employees	34730	39.54	3312	40.32
Share of highly educated	34730	0.21	3312	0.26
Share of high.ed. in wage bill	34730	0.25	3312	0.31
Share of female	34730	0.31	3312	0.29
Sales	38618	17244	3769	20245
Capital/Labour- ratio	29892	153.59	2904	118.13
Value Added	34620	11177	3298	14497
Export share	36037	0.20	3584	0.25
R&D unit	39382	0.00	3880	0.01

Table 4 Difference in the characteristics of Acquired and Non-acquired plants before and after acquisition

	Acquired plants		Non-acquired plants		Difference	
Variable	Obs	Mean	Obs	Mean		%
Pre-acquisition characteristics (from t=0)						
Size_0	355	177.07	14407	116.91	60.16	33.98
Log(sales)_0	355	9.57	14407	8.91	0.66	6.86
K/L_0	325	188.11	12902	144.40	43.71	23.24
Y/L_0	354	17825	14357	10570	7254	40.70
Export/sales_0	355	0.33	14407	0.24	0.09	28.20
Av. age_0	354	40.47	14362	39.67	0.80	1.97
Av. school_0	354	11.76	14362	11.48	0.29	2.43
Av. tenure_0	354	12.37	14362	11.17	1.20	9.71
Female-share_0	354	0.29	14362	0.32	-0.02	-8.41
Post-acquisition characteristics (from t=1)						
Size	355	172.14	14407	117.03	55.11	32.02
Log(sales)	355	9.64	14330	8.95	0.69	7.12
K/L	325	138.18	12925	141.88	-3.70	-2.68
Y/L	355	20372	14396	10776	9596	47.11
Export/sales	355	0.32	14330	0.24	0.09	26.87
Av. Age	355	40.50	14407	40.04	0.46	1.14
Av. School	355	11.77	14407	11.52	0.25	2.15
Av. tenure	355	12.36	14407	11.49	0.87	7.05
Female-share	355	0.28	14407	0.31	-0.03	-10.70
Wages of less educated from -1 to +3						
Log. Wage_1	352	9.35	14118	9.25	0.10	1.03
Log. Wage_0	343	9.36	14087	9.27	0.09	0.92
Log. Wage1	344	9.38	14125	9.29	0.09	0.99
Log. Wage2	350	9.42	14120	9.30	0.12	1.26
Log. Wage3	352	9.43	14075	9.32	0.11	1.13
Wages of highly educated from -1 to +3						
Log. Wage_1	251	9.70	7558	9.66	0.04	0.43
Log. Wage_0	243	9.70	7705	9.66	0.04	0.40
Log. Wage1	250	9.72	7894	9.67	0.05	0.54
Log. Wage2	249	9.75	8044	9.68	0.07	0.72
Log. Wage3	249	9.77	8100	9.69	0.07	0.74
Share of highly educated workers in employment from -1 to +3						
Empl.share_1	355	0.24	14407	0.20	0.04	16.74
Empl.share_0	354	0.25	14362	0.20	0.05	18.87
Empl.share1	355	0.24	14407	0.21	0.04	15.70
Empl.share2	355	0.25	14407	0.21	0.04	14.77
Empl.share3	355	0.24	14407	0.21	0.02	10.04
Share of highly educated workers in total wage bill from -1 to +3						
Wb.share_1	355	0.29	14407	0.24	0.04	15.46
Wb.share_0	354	0.30	14362	0.25	0.05	16.87
Wb.share1	355	0.29	14407	0.25	0.04	14.17
Wb.share2	355	0.30	14407	0.26	0.04	13.82
Wb.share3	355	0.29	14407	0.26	0.03	10.43

Table 5 Effect of foreign ownership on average wages

	Wages of less educated workers						Wages of highly educated workers					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	Coef.	t-stat.	Coef.	t	Coef.	t	Coef.	t-stat.	Coef.	t	Coef.	T
Foreign	0.032	(10.01)	0.011	(4.08)	0.002	(0.72)	0.054	(12.27)	0.014	(2.28)	0.003	(0.53)
Foreign_1					0.019	(4.94)					0.010	(1.53)
Foreign_2					0.000	(0.15)					0.017	(2.69)
Plant size	0.000	(25.69)	0.000	(7.55)	0.000	(7.59)	0.000	(9.14)	0.000	(5.55)	0.000	(5.62)
Av. School	0.768	(11.59)	0.302	(4.23)	0.302	(4.23)	1.673	(10.85)	2.239	(11.34)	2.227	(11.29)
Av. Sch. ^2	-0.033	(-10.64)	-0.014	(-4.08)	-0.014	(-4.08)	-0.052	(-10.15)	-0.072	(-10.95)	-0.071	(-10.89)
Av. Age	0.031	(8.15)	0.011	(3.05)	0.010	(2.99)	0.079	(12.20)	0.052	(7.61)	0.051	(7.59)
Av. Age ^2	-0.000	(-7.95)	-0.000	(-3.03)	-0.000	(-2.97)	-0.000	(-10.68)	-0.000	(-6.07)	-0.000	(-6.05)
Av. Tenure	0.000	(1.33)	0.000	(1.67)	0.000	(1.75)	0.001	(3.80)	0.000	(0.77)	0.000	(0.77)
Av. Tenure^2	-0.000	(-9.11)	0.000	(0.70)	0.000	(0.62)	-0.000	(-0.36)	-0.000	(-0.33)	-0.000	(-0.31)
Female-share	-0.264	(-56.71)	-0.106	(-9.28)	-0.106	(-9.28)	-0.139	(-18.27)	0.168	(7.08)	0.167	(-7.03)
K/L	0.000	(13.82)	0.000	(0.86)	0.000	(0.92)	0.000	(1.70)	-0.000	(10.36)	-0.000	(10.34)
Export-share	-0.005	(-1.79)	-0.002	(-0.77)	-0.002	(-0.74)	0.013	(3.71)	-0.007	(-1.44)	-0.007	(-1.44)
Constant	4.439	(12.25)	7.366	(19.16)	7.372	(19.19)	-5.506	(-4.69)	-8.991	(-6.41)	-8.902	(-5.96)
Time Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Industry effects	Yes		No		No		Yes		No		No	
Region Effects	Yes		No		No		Yes		No		No	
Plant Effects	No		Yes		Yes		No		Yes		Yes	
Number of obs.	21630		21630		21630		12186		12186		12186	
R-sq	0.491		0.501	within	0.502	within	0.366		0.255	within	0.256	Within

The dependent variable is the logarithm of the average monthly wage of the skill group in the plant. Schooling, age and tenure are measured as averages in the skill group in the plant. Foreign is a dummy variable which indicates whether plant is foreign-owned in current year, Foreign_1 is a dummy variable which indicates whether plant was foreign owned in the previous year, and Foreign_2 is a dummy variable which indicates whether plant was foreign owned two periods before.

Table 6 Effect of foreign ownership on share of highly educated workers in employment/total wage bill

	Share of highly educated workers in employment						Share of highly educated workers in wage bill					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	Coef.	t-stat.	Coef.	t	Coef.	t	Coef.	t-stat.	Coef.	t	Coef.	t
Foreign	0.007	(1.84)	0.004	(1.53)	0.003	(0.86)	0.011	(2.54)	0.004	(1.42)	0.002	(0.69)
Foreign_1					0.002	(0.74)					0.003	(0.83)
Foreign_2					0.000	(0.03)					0.000	(0.09)
Log(W_{hed}/W_{led})	-0.010	(-1.29)	-0.037	(-6.34)	-0.037	(-6.35)	0.156	(18.66)	0.130	(20.80)	0.130	(20.78)
Log(K)	-0.029	(-22.49)	0.001	(0.37)	0.001	(0.38)	-0.030	(-21.77)	0.001	(0.41)	0.001	(0.42)
Log(Y)	0.007	(3.31)	-0.004	(-3.62)	-0.005	(-3.62)	0.006	(2.57)	-0.006	(-3.95)	-0.006	(-3.94)
Log(sales)	0.024	(11.39)	0.001	(0.63)	0.001	(0.62)	0.027	(11.75)	0.001	(0.80)	0.001	(0.78)
Export-share	0.017	(3.59)	0.013	(3.49)	0.013	(3.49)	0.019	(3.74)	0.014	(3.32)	0.014	(3.32)
Constant	0.043	(0.45)	0.287	(15.43)	0.287	(15.42)	-0.023	(-0.22)	0.293	(14.84)	0.293	(14.83)
Time Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Industry effects	Yes		No		No		Yes		No		No	
Region Effects	Yes		No		No		Yes		No		No	
Plant Effects	No		Yes		Yes		No		Yes		Yes	
Observations	11533		11533		11533		11533		11533		11533	
R-sq	0.209		0.084		0.084		0.227		0.091		0.091	

The dependent variable is the employment or wage bill share of highly educated workers in a plant. Foreign is a dummy variable which indicates whether plant is foreign-owned in current year, Foreign_1 is a dummy variable which indicates whether plant was foreign owned in the previous year, and Foreign_2 is a dummy variable which indicates whether plant was foreign owned two periods before.

Table 7 Probit model to estimate the propensity score

Dependent variable: Probability of foreign acquisition	Coef.	Std. Err.	P>z
Plant size_0	-0,001	0,000	0.005
(Plant size_0)^2	0,000	0,000	0.008
Log(sales)_0	0,126	0,028	0.000
Export/sales_0	0,880	0,296	0.003
(Export/sales _0)^2	-0,624	0,318	0.050
Industry exporter-share_0	-1,015	0,198	0.000
Industry foreign-share _0	1,731	0,252	0.000
Log(Y^{region})_0	0,041	0,027	0.131
Log(wage)_1	0,229	0,188	0.224
Av. School_1	0,058	0,033	0.081
Av. Age_1	-0,011	0,012	0.346
Av. Tenure_1	0,092	0,025	0.000
(Av. Tenure_1)^2	-0,002	0,001	0.021
Ind. Dummies	Yes		
Region dummies	Yes		
Year dummied	Yes		
Pseudo r-square	0.1643		
LR chi2(31)	550.17		
Observations	14762	100%	
Treated	355	2,40%	
Control	14,407	97.60%	

The explanatory variables are from pre-acquistion periods. _0 in end of the variable refers to period just before the acquisition (0), and _1 to period 1-2 years before the acquisition (-1).

Table 8 Effect of foreign acquisition on average wages of less educated workers: matching sample

Method:	**Cross-section matching**			**Difference-in-differences matching**		
Outcome	Regression (OLS)	Nearest- Neighbor	Kernel	Regression (OLS)	Nearest- Neighbor	Kernel
Log. average wage at t = 1						
ATT	-0.009	-0.028	0.060	0.006	0.008	0.006
t-stat	(-1.50)	(-1.97)	(6.79)	(1.24)	(0.76)	(0.73)
Treated		333	333		333	333
Controls (obs.)	(13499)	307	13276	(13499)	307	13276
Log. average wage at t = 2						
ATT	0.015	-0.006	0.084	0.029	0.029	0.030
t-stat	(2.57)	(-0.47)	(7.22)	(5.71)	(2.98)	(3.91)
Treated		333	333		333	333
Controls (obs.)	(13499)	307	13276	(13499)	307	13276
Log. average wage at t = 3						
ATT	0.007	-0.018	0.074	0.022	0.018	0.020
t-stat	(1.25)	(-1.33)	(6.82)	(3.99)	(1.77)	(2.72)
Treated		333	333		333	333
Controls (obs.)	(13499)	307	13276	(13499)	307	13276

First 3 columns report the results of regression and matching analysis where the dependent variable is the level of outcome (e.g. wages of the skill group) in the period right after possible acquisition (t=1), 1-2 years after possible acquisition (t=2) and 2-3 years after the possible acquisition (t=3). Next 3 columns report the results of regression and matching analysis where the dependent variable is the difference between the outcome in the year just before the possible acquisition (0) and in different post-acquisition years (1,2, and 3). The explanatory variables in regressions are exactly the same as are used to estimate the propensity score, which is used in the matching analysis. These are reported in table 7. Common support restriction is imposed in all regressions and matching. T-statistics are reported in parenthesis. For matching results we report the boostrapped t-statistic.

Table 9 Effect of foreign acquisition on average wages of highly educated workers: matching sample

Method:	**Cross-section matching**			**Difference-in-differences matching**		
Outcome	Regression (OLS)	Nearest- Neighbor	Kernel	Regression (OLS)	Nearest- Neighbor	Kernel
Log. average wage at t = 1						
ATT	0.013	0.026	0.036	0.017	0.013	0.015
t-stat	(1.29)	(1.60)	(3.41)	(1.95)	(0.83)	(1.02)
Treated		212	212		212	212
Controls (obs.)	(6726)	198	6031	(6726)	198	6031
Log. average wage at t = 2						
ATT	0.019	0.034	0.046	0.024	0.021	0.025
t-stat	(1.97)	(2.25)	(5.62)	(2.51)	(1.30)	(1.61)
Treated		212	212		212	212
Controls (obs.)	(6726)	198	6031	(6726)	198	6031
Log. average wage at t = 3						
ATT	0.026	0.044	0.056	0.031	0.032	0.035
t-stat	(2.65)	(2.92)	(5.74)	(3.06)	(1.93)	(2.08)
Treated		212	212		212	212
Controls (obs.)	(6726)	198	6031	(6726)	198	6031

First 3 columns report the results of regression and matching analysis where the dependent variable is the level of outcome (e.g. wages of the skill group) in the period right after possible acquisition (t=1), 1-2 years after possible acquisition (t=2) and 2-3 years after the possible acquisition (t=3). Next 3 columns report the results of regression and matching analysis where the dependent variable is the difference between the outcome in the year just before the possible acquisition (0) and in different post-acquisition years (1,2, and 3). The explanatory variables in regressions are exactly the same as are used to estimate the propensity score, which is used in the matching analysis. These are reported in table 7. Common support restriction is imposed in all regressions and matching. T-statistics are reported in parenthesis. For matching results we report the boostrapped t-statistic.
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Table 10 Effect of foreign acquisition on the share of highly educated workers in employment: matching sample

Method:	**Cross-section matching**			**Difference-in-differences matching**		
Outcome	Regression (OLS)	Nearest- Neighbor	Kernel	Regression (OLS)	Nearest- Neighbor	Kernel
Log. average wage at t = 1						
ATT	0.004	0.000	0.027	-0.007	-0.004	-0.007
t-stat	(0.74)	(0.02)	(4.01)	(-1.58)	(-0.55)	(-1.16)
Treated		354	354		354	354
Controls (obs.)	(14086)	329	13704	(14086)	329	13704
Log. average wage at t = 2						
ATT	0.002	0.002	0.025	-0.008	-0.002	-0.009
t-stat	(0.45)	(0.20)	(3.22)	(-1.79)	(-0.27)	(-1.43)
Treated		354	354		354	354
Controls (obs.)	(14086)	329	13704	(14086)	329	13704
Log. average wage at t = 3						
ATT	-0.010	-0.014	0.013	-0.020	-0.018	-0.022
t-stat	(-1.64)	(-1.11)	(2.06)	(-3.94)	(-2.26)	(-3.17)
Treated		354	354		354	354
Controls (obs.)	(14086)	329	13704	(14086)	329	13704

First 3 columns report the results of regression and matching analysis where the dependent variable is the level of outcome (e.g. wages of the skill group) in the period right after possible acquisition (t=1), 1-2 years after possible acquisition (t=2) and 2-3 years after the possible acquisition (t=3). Next 3 columns report the results of regression and matching analysis where the dependent variable is the difference between the outcome in the year just before the possible acquisition (0) and in different post-acquisition years (1,2, and 3). The explanatory variables in regressions are exactly the same as are used to estimate the propensity score, which is used in the matching analysis. These are reported in table 7. Common support restriction is imposed in all regressions and matching. T-statistics are reported in parenthesis. For matching results we report the boostrapped t-statistic.

Table 11 Effect of foreign acquisition on the share of highly educated workers in wage bill: matching sample

Method:	**Cross-section matching**			**Difference-in-differences matching**		
Outcome	Regression (OLS)	Nearest- Neighbor	Kernel	Regression (OLS)	Nearest- Neighbor	Kernel
Log. average wage at t = 1						
ATT	0.004	0.001	0.030	-0.007	-0.004	-0.007
t-stat	(0.72)	(0.06)	(3.99)	(-1.46)	(-0.48)	(-1.11)
Treated		354	354		354	354
Controls (obs.)	(14086)	329	13704	(14086)	329	13704
Log. average wage at t = 2						
ATT	0.004	0.005	0.029	-0.007	0.000	-0.008
t-stat	(0.61)	(0.36)	(3.19)	(-1.43)	(0.06)	(-1.09)
Treated		354	354		354	354
Controls (obs.)	(14086)	329	13704	(14086)	329	13704
Log. average wage at t = 3						
ATT	-0.008	-0.011	0.017	-0.019	-0.016	-0.020
t-stat	(-1.28)	(-0.82)	(2.46)	(-3.46)	(-1.84)	(-2.88)
Treated		354	354		354	354
Controls (obs.)	(14086)	329	13704	(14086)	329	13704

First 3 columns report the results of regression and matching analysis where the dependent variable is the level of outcome (e.g. wages of the skill group) in the period right after possible acquisition (t=1), 1-2 years after possible acquisition (t=2) and 2-3 years after the possible acquisition (t=3). Next 3 columns report the results of regression and matching analysis where the dependent variable is the difference between the outcome in the year just before the possible acquisition (0) and in different post-acquisition years (1,2, and 3). The explanatory variables in regressions are exactly the same as are used to estimate the propensity score, which is used in the matching analysis. These are reported in table 7. Common support restriction is imposed in all regressions and matching. T-statistics are reported in parenthesis. For matching results we report the boostrapped t-statistic.

Table 12 Effect of foreign acquisition on average wages by educational category: difference-in-differences matching results

Difference-in-differences matching/regression results:									
	Regression (OLS)			Nearest-neigbour matching			Kernel matching		
Education:	ATT	t-stat	Obs.	ATT	t-stat	Treat/contr	ATT	t-stat	Treat/contr
Basic education									
T=1	-0.001	(-0.10)	13612	0.001	(0.15)	338/318	0.001	(0.07)	338/13269
T=2	0.030	(4.91)	13612	0.036	(3.68)	338/318	0.031	(4.01)	338/13269
T=2	0.019	(2.94)	13612	0.016	(1.52)	338/318	0.017	(2.38)	338/13269
Vocational education									
T=1	0.007	(1.29)	13862	0.008	(0.79)	345/319	0.006	(0.81)	345/13657
T=2	0.036	(6.27)	13862	0.039	(3.85)	345/319	0.037	(4.76)	345/13657
T=2	0.023	(3.73)	13862	0.029	(2.76)	345/319	0.022	(3.08)	345/13657
Lower university education									
T=1	0.007	(0.87)	13272	0.010	(0.73)	327/309	0.007	(0.62)	327/12405
T=2	0.030	(3.30)	13272	0.026	(1.67)	327/309	0.033	(3.32)	327/12405
T=2	0.031	(3.19)	13272	0.032	(2.21)	327/309	0.041	(4.18)	327/12405
Higher university education									
T=1	0.029	(1.81)	6826	0.044	(1.77)	214/198	0.024	(1.10)	214/6070
T=2	0.040	(2.28)	6826	0.059	(2.04)	214/198	0.036	(1.90)	214/6070
T=2	0.037	(1.94)	6826	0.069	(2.14)	214/198	0.036	(1.62)	214/6070

Common support restriction imposed in all regressions and matching. The dependent variables is the pre-and post acquisition difference in the average earnings of the educational category in a plant. T=1 refers to difference between the pre-acquisition wages and the wages at the period just after acquisition (1). T=2 refers to difference between the pre-acquisition wages and the wages at the period 1-2 years after acquisition (2). T=3 refers to difference between the pre-acquisition wages and the wages at the period 2-3 years after acquisition (3). The explanatory variables in regressions are exactly the same as are used to estimate the propensity score, which is used in the matching analysis. These are reported in table 7. Common support restriction is imposed in all regressions and matching. T-statistics are reported in parenthesis. For matching results we report the boostrapped t-statistic.

IV How Destructive is Creative Destruction? The Costs of Worker Displacement*

Abstract

This study analyses the costs of worker displacements using a matched employer-employee database spanning the entire Norwegian economy. We find that workers who are displaced from their jobs work on average 3.2 months less in the following year as compared to similar workers who were not displaced. Seven years after displacement the average employment reduction is only a few days per year. Earnings are on average reduced by 2-5 percent in the first year after displacement. This effect decreases slowly, and is 1-2 percent seven year after displacement. The negative employment effect is in the short run weaker for workers that were displaced by plant exit than for those displaced from troubled firms. This is consistent with the latter group searching less intensely for a new job because they hope to be recalled. We find that workers with less than 10 years of schooling, and workers displaced from small plants are more vulnerable than other groups.

*Joint work with Jarle Møen and Kjell G. Salvanes.

1 Introduction

In competitive markets there is continuos entry and exit of firms. Productive and innovative firms expand and less productive firms downsize. This is the process of creative destruction, widely thought to be the most important source of long term economic growth.[1] If creative destruction is to be more "creative" than "destructive", large amounts of productive inputs must successfully be reallocated between firms. Such reallocation is not frictionless. In particular, there might be significant costs related to worker reallocation. How large are these costs and who bears the burden of restructuring? More precisely, how long are workers unemployed after loosing their job due to plant exits or downsizing? How are their future earnings affected? What characterize workers who are quickly reemployed and what characterize those that end up as long term unemployed? These are important questions for policy makers when firms, unions and local communities lobby for subsidies to save threatened jobs.

The majority of US studies analyzing the costs of involuntary job loss, indicate that earnings and employment losses of displaced workers are large and persistent.[2] Earnings losses are estimated to be up to 25 percent four years after loosing the job. Studies of displaced workers in European countries are fewer and the results less clear.[3] The bulk of previous studies, whether European or US, use individual or household level survey data. Usually, only workers still in employment are included in such surveys, and this will bias the results if displacement is correlated with the probability of leaving the labour force. Most surveys also lack a longitudinal dimension, and hence cannot follow workers over time.

This paper analyzes short term and long term costs of worker displacement using a large administrative matched employer-employee data set. The

[1] See e.g. Haltiwanger et al. (2000).
[2] See surveys by Hamermesh (1987), Fallick (1996) and Kletzer (1998).
[3] Cf. the studies in Kuhn (2002).

data are a census of the Norwegian population of workers and plants for the years 1986-2000.

In order to measure the causal effect of displacement, we would ideally compare the displaced workers' earnings and employment histories with what would have happened without displacement. Obviously, we do not have information about workers as displaced and in a job at the same time. The general solution to this problem is to use comparison groups to construct the counterfactual situation, i.e. use information about the non-displaced workers to approximate the outcome for displaced workers in the non-displacement situation. We follow the standard approach in the literature and start out using plant exits to identify exogenous separations. However, exiting plants are not a random sample of plants, and we exploit the richness of our data to construct what can be thought of as "twin firms" contrasting, within a regression framework, the labour market experience of workers from plants that are similar along many observable dimensions such as plant size, industry and local labour market conditions. The difference in outcomes for similar workers in exiting plants, the treatment group, and in continuing plants, the control group, identifies the effect of displacement. We also look at alternative treatment groups, distinguishing between workers who lost they jobs at the moment when their plant closed down, those who separated from the plant in the period before it closed down, and incidents of mass-layoffs i.e. workers leaving plants that downsize significantly from one year to the next without exiting. Based on descriptive evidence on the pattern on earnings and employment, we include workers leaving plants that are about to exit as wells workers leaving plants during a mass-layoff incident in the treatment group.

We can follow workers and their earnings even if they leave the labour force. This is possible because we have data on *all* 16-74 year old Norwegians for 1986-2000. We argue that in order to examine the true costs of displacement, it is important to work on population data, because displacement might have an impact on the probability of leaving the labour force permanently. It is also important to allow workers in the comparison group to leave the labour force. This group represents the "ongoing economy", and a significant number of workers leave the labour force for reasons other than having been displaced.

In addition to estimating the average effects of displacement, we analyze heterogeneity in displacement effects by observable pre-displacement worker, plant, and labour market characteristics. Are old workers more vulnerable than young workers? What happens to workers in "sunset" industries, i.e. industries with negative long term growth? What happens to workers that are displaced from firms which are dominant in a local labour market? When examining effects by pre-displacement characteristics, we can better understand the reasons behind displacement costs. This may aid policy makers in designing policies that promote growth and restructuring.

We find that displacement significantly increases the probability of leaving the labour force. Those displaced workers who remain in the labour force work on average 3.2 months less in the following year as compared to similar workers who were not displaced. Seven years after displacement the average employment reduction is only a few days per year. Earnings are on average reduced by 2-5 percent in the first year after displacement. This effect decreases slowly, and is 1-2 percent seven year after displacement. The negative employment effect is in the short run weaker for workers that were displaced by plant closing down than for those displaced from troubled firms. Workers with less than 10 years of schooling, and workers displaced from small plants are more vulnerable than other groups.

The rest of the paper is organized as follows. Section 2 discusses the previous literature. Section 3 describes the data and our definition of key variables. Section 4 gives details on the sample construction. Section 5 gives details on our identification strategy. Section 6 discusses selection issues. Section 7 presents descriptive evidence. Section 8 describes the results from our regression analysis, and the last section concludes the paper.

2 Previous literature

The costs of displacement have been studied intensively for the last 25 years[4]. Until recently most of these studies analyzed displacement in the US labour market. The results indicate substantial negative earnings effects both in the short and long term. The earnings loss starts at least three years before displacement and persist many years after. 4-5 years after the displacement the loss is still 10-25%. The approach of using comparison groups for measuring the effect of displacement, i.e. the loss is measured as the earnings change for the displaced workers as compared to an earnings change for a control group that was not displaced, started in the early 1990s with papers by Ruhm (1991) and Jacobson et al. (1993). The previous literature compared earnings for the same workers before and after being displaced. Jacobson et al. (1993) define workers as displaced if they left a firm that experienced a significant downsizing. As a comparison group they used workers who did not separate from their firms. Their findings suggest that displaced workers suffer large and long-lasting earnings reductions after displacement. Five years after displacement, average quarterly earning losses were 25%. One limitation of the analysis is its use of data from one single state, Pennsylvania. Displacement in a state dominated by traditional manufacturing industries may not be representative of the nation as a whole.

Ruhm (1991) and Stevens (1997) avoid this problem by using a nationally based sample of displaced workers from the Panel Study of Income Dynamics (PSID). Ruhm (1991) examines the effect of job displacement on unemployment. The treatment group are the workers who were displaced during a "base year". The comparison group consists of workers loosing jobs at a later date. This allows him to control for unobservable heterogeneity between

[4]See overviews by Hamermesh, 1987; Fallick, 1996; Kletzer, 1998 and Kuhn, 2002.

displaced and non-displaced workers (to the extent that persons displaced in different periods are similar). The results indicate that displaced workers suffer significant reduction in employment after displacement, but this effect is not permanent. The difference seems to fade away within 4 years.

Stevens (1997) examines the long-term effects of job displacement on earnings. A worker is labeled displaced if he or she left the previous job due to plant or business closing or due to being laid off or fired. The comparison group consists of never-displaced workers. She found that the effects of displacement are quite persistent, with earnings and wages remaining approximately 9% below their expected levels six years or more after displacement. She also shows that much of this persistence can be explained by additional job losses in the years following displacement. Workers who avoid additional separations have earnings and wage losses 1-2 % six or more years after the initial displacement.

Kletzer at al. (2001) use data from the National Longitudinal Survey of Youth (NSLY) to study the long-term effects of job displacement for young workers. They define a worker as displaced if he or she was no longer working at a reported job and the reason for the job ending was "layoff" or "plant closing". They include only the first observed job displacement for each individual during the survey period. Thus, the future job displacements are not controlled for and potential future displacements are viewed as a cost of the initial displacement. They found that the earnings and wage losses associated with job displacement for young workers are large, although somewhat smaller and less persistent than the losses found by others for older and more established workers.

In contrast to the large supply of US studies, studies on European data on the costs of job displacement have been more scarce. Like in the US studies, the main focus has been on the earnings losses following displacement. The results of these studies are hard to summarize as they appear to be rather mixed. On average smaller short term and long term earnings losses have been reported than in the US. The European studies support the finding that those who experience further job losses following displacement experience larger earnings losses than those who do not.

Borland et al. (2002) examine the consequences of job loss for displaced workers in Britain utilizing the British Household Panel Survey. Workers are defined as displaced if they left their previous job due to redundancy or dismissal. In order to calculate the earning loss of displaced workers the authors compare displaced workers' earnings in the current job with their earnings in the previous job. They found that weekly wages of the average displaced worker is around 10 percent lower in the new job than in the job lost. Part of the loss is due to the fact that displaced workers are more likely to end up in part time jobs. If the displaced worker moves from one full time job to another, the wage loss is only 4%, and for those who move directly to a new job the wage loss is 2%.

Bender et al. (2002) examine the effects of worker displacement in France and Germany. They exploit large administrative based data from both countries, that match workers to their employers. They focus on prime-age males with more than four years of seniority. Displacement is defined as a separation that results from the closure of the employing firm. In Germany they also define worker as displaced if he or she separates from a downsizing plant. Using the French data they found no negative post-displacement earnings effects, while in Germany the displacement seem to lead to 1-2 percent wage decrease in the years after its occurrence. Burda and Mertens (1998) also report on average small wage effects following displacement in Germany, although highly paid workers experience an earnings reductions prior to displacement that is more similar to the US results.

Albaek et al. (2002) examine the effects of job displacement in Belgium and Denmark. For both countries, displaced worker's earnings drop more than those of the worker's in two comparison groups in the year immediately following job displacement. The difference is smaller when using the non-displaced worker in downsizing firms as the comparison group.

In a very recent paper, Carneiro and Portugal (2004) use administrative matched employer-employee data to analyze earnings losses of displaced workers in Portugal. In contrast to most European studies they find substantial earnings losses following displacement. The earnings loss is 8-11% after four years. This is within the lower bound of the US results. They also find that the losses depend on spells of unemployment as well as on worker and firm characteristics.

Most data sets used in displacement studies cover only workers that are in the labour force[5]. This may lead to a serious underestimate of the costs of displacement since an obvious consequence of job displacement is that workers might be pushed out of labour force permanently. Chan and Stevens (2001) focus on this question. They examine the employment patterns of older workers (50+) after job loss using US data from the Health and Retirement Study. They focus on workers who have lost their jobs due to plant closing or due to layoff, and find that a job loss results in large and lasting effects on future employment probabilities. Four years after a job loss, at age 55+, the employment rate of displaced workers remains 20 percent point below the employment rate of similar non-displaced workers.

Studies examining employment consequences of job displacement in Europe are very scarce. The few ones that analyze the joblessness after displacement mainly provide descriptive information on the duration of non-employment, or study the determinants which affect this duration. Abbring et al. (2002) report that most of the displaced workers in the sample of workers in Netherlands move directly to new jobs, and very few suffer a period of joblessness that lasts for more than one year. Bender et al. (2002) found that displaced workers are less likely to have non-employment spells after separation than other separators in France and Germany. They are also

[5]One of the commonly used data sets in the US, for example, the PSID, has only information on houshold heads (thus mostly men) with positive earnings in every year.

leave non-employment faster. Albaek et al (2002) find that in Belgium, re-employment is significantly more likely for high-wage workers, young workers and for high tenure-workers. This positive effect of tenure may reflect greater advance notice and other re-employment assistance provided to senior workers.

3 Data and definition of key variables

The data on workers used in our study comes from administrative registers and are prepared for research by Statistics Norway. It covers all 16-74 year old Norwegian residents in the years 1986-2000. There is information about employment relationships, taxable income, educational attainment, labour market status, and a set of demographic variables such as gender, age and marital status. We work only on males in this paper. A unique person identification code allows us to follow workers over time. Likewise a unique plant code allows us to identify each employed worker's plant and examine whether the plant is downsizing or closing down. Plant and local labour market characteristics such as industry, size and the rate of unemployment is also available. The match between workers and plants is in May in the observation year.[6]

The data allow us to distinguish clearly between *stayers* and *separators*. We define a worker as a separator at time t if at time $t + 1$ he no longer has the same plant identification number. Following the previous literature, displaced workers are understood to be individuals, who *involuntary* separate from their jobs by exogenous shocks. Hence, workers fired for cause are not included.[7] As mentioned in the introduction, we define displaced workers as workers separating from a plant that closes down or goes through significant employment reduction in the period when the separation occurs. We distin-

[6] November from 1996.

[7] Cf. e.g. Fallick (1996).

guish between three different categories of displaced workers: "Exit-layoffs", "early-leavers" and "downsizing plant separators". A worker is classified as an *exit-layoff* if he works in an exiting plant at the time the plant is last observed.[8] A worker is classified as an *early-leaver* at time t if he separates between t and $t+1$ from a plant that exits between $t+1$ and $t+2$. A workers is classified as a *downsizing plant separator* at time t if he separates from a plant with more than five employees that reduce employment by 30 percent or more from t to $t+1$.[9]

The main analysis examine the average effect of displacement on employment and earnings. In order to account for unemployment spells and part time jobs, employment is measured as months of full time equivalent employment over the year.[10] Earnings is measured as annual taxable labour income.

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[8] A plant is defined as an exiting plant in year t if it is present in year t but absent in $t+1$ and in $t+2$. If possible, we also check that the plants do not reappear after $t+2$. We drop all workers in plants that reappear. Furthermore, we check whether the workers whose plant exited between t and $t+1$, work in a new plant at time $t+1$ with a new identification code, but with exactly the same workers as in the exiting plant. All workers in such plants are also dropped. Such "false" plant exits appear when a plant moves to a different municipality.

[9] A similar downsizing plant definition has been used in many previous studies, e.g. Albaek et al. (2002). The downsizing category does not include early-leavers who separate from downsizing plants that are exiting in the future. Note also that for small plants, a 30 percent reduction is not a "mass layoff". We have decided, however, that an approach without a special size restriction for defining downsizing plants is better than having an arbitrary size cut and including all workers leaving smaller plants in the non-displaced comparison group. We are using 5 employee size cut (i.e. including only plants with at least 5 workers) for *all* plants in the base year sample.

[10] Part time employment is handled as follows: Y_{it} = months of employment if a worker is working more than 30 hours a week, Y_{it} = (months of employment)$*0,5$ if a worker is working 20-29 hours a week and Y_{it} = (months of employment)$*0,1$ if a worker is working less than 20 hours a week.

4 Sample construction

The sample used in our main analysis is constructed by first identifying all male workers between age 25 and 55 who were full-time employed in manufacturing plants with at least five workers in 1991, our "base year". Next, we keep only the workers that were in the labour force and *did not* experience a displacement incident between 1988 and 1991.[11] The sample obtained in this way consists of 103 240 workers. We trace these workers' employment history three years before and seven years after 1991. This gives us an 11 year long balanced panel.[12]

Using the definitions explained in the previous section, workers are divided into five categories based on what happens between 1991 and 1992: Exit-layoffs, early-leavers, downsizing-plant-separators, other separators and non-separators (stayers). The first three categories define our treatment group: Workers who were full-time employed in manufacturing in May 1991 and were displaced from their jobs between May 1991 and May 1992. These workers will be referred to as displaced in 1991. The comparison groups are those working full-time in manufacturing in May 1991 that were *not* displaced from their jobs between May 1991 and May 1992, i.e. stayers and other separators.

Figure 1 and Table 1 show the plant exit rate and the share of workers experiencing a displacement incident along with unemployment and growth for the Norwegian economy in 1986-2000. Plant exits and displacement are positively correlated, and they are both negatively correlated with growth and positively correlated with the change in the unemployment rate. Hence displacements are counter cyclical.[13] Note that our base year 1991 is in the

[11] In section 8.5 we also use other years than 1991 as base year, checking robustness and analysing business cycle effects.

[12] The reason we do not use the years 1986, 1987, 1999 and 2000 is that information about months of unemployment is missing.

[13] The correlation between plant exit and displacement is 0.57 and significant at the 5-percent level. The correlation between plant exit and growth is -0.47 and significant at the

middle of a major recession lasting from about 1988 to 1993.

Table 2A reports the mean values of the main pre-displacement variables for different worker categories. Overall, the observable differences between the various groups are small. This is what we want to obtain by our sample selection procedure, conditioning on workers being in the labour force and not displaced from their jobs in the three years prior to our base year 1991. Displaced workers are slightly younger and more educated than non-displaced workers, and they have 1.3 year shorter tenure. Furthermore, displaced workers earn slightly more than non-displaced workers both one and three years prior to displacement. Exit-layoffs seem slightly more "senior" than downsizing separators and early-leavers. Among the non-displaced workers, stayers are more senior than separators.

Table 2B gives plant level descriptive statistics. We see that the average plant size in the sample, 42 workers, is small. This reflects the general industry structure in Norway consisting mostly of small and medium size firms. Exiting and downsizing plants are somewhat smaller than other plants, having on average 31 and 37 workers respectively. Average tenure is 2.1 year shorter in exiting plants and 1.1 year shorter in downsizing plants compared to the overall average. Both of these patterns are consistent with many of the exiting plants being young. On average, however, exiting plants are as old as 16 years, and downsizing plants are 18 years old. Other plants are on average 20 years old.

10-percent level. The correlation between displacement and growth is -0.23. The correlation between plant exit and change in the unemployment rate is 0.54 and significant at the 5-percent level. The correlation between displacement and change in the unemployment rate is 0.08.

5 Specifications

We start our analysis by investigating the effect of displacement on the probability of being permanently out of the labour force[14] one and seven years after displacement. We use the following probit specification:

$$P(E_i) = \Phi(\mathbf{X}_i\beta + Z_i\gamma + D_i\delta) \quad (1)$$

E (exit) is a dummy variable for being out of the labour force, $\mathbf{X}$ is a vector of observable pre-and post-displacement worker characteristics. Z is a vector of plant characteristics and local labour market characteristics identifying "twin plants" and D is a dummy variable for having been displaced. We expand specification (1) by distinguishing between the three subcategories of displaced workers, exit-layoffs, early leavers and downsizing separators.

Having explored how displacement affects labour force participation, we exclude workers that are permanently out of the labour force[15] from our sample before analyzing the average effect of displacement on months of employment and earnings for those in the labor force. If not restricting the sample in this way, our estimates would be averages across workers in and out of the labour force, something that would not be particularly interesting figures. We want to establish the probability that a worker is pushed out of the labour force in the aftermath of a displacement incident, and the average effect on employment and earnings for those that are not pushed out.

Analyzing this second question, our main specification is

$$Y_{it} = \mathbf{X}_{it}\beta + Z_{it}\gamma + \sum_{j=-3}^{7} D_{it-j}\delta_j + \tau_t + \alpha_i + \epsilon_{it}. \quad (2)$$

[14] By permanently out of the labour force we mean that a worker is never again observed in the labour force within the time horizon of our panel. One year after displacement, this horizon is seven years. Seven years after displacement, therefore, we cannot distinguish between workers permanently and temporarily out of the labour force.

[15] I.e. we exclude workers not in the labour force at year $t + 7$.

Y is labour market outcome, either months of employment or the natural logarithm of annual taxable labour income. $\mathbf{X}$ and Z are, as above, vectors of observable worker and firm characteristics. Time dummies, τ, are included, and in some specifications also individual fixed effects, α_i. The variables of main interest are the displacement variables, D_{it-j}. These are dummy variables indicating whether a displacement occurs at time $t-j$, t being the observation year. Job loss is allowed to affect labour market outcomes four years before its occurrence and seven years after its occurrence, hence $j = -3..., 0, ...7$. The treatment group is workers who were working at $t = 0$, and were displaced from their jobs between $t = 0$ and $t = 1$. The control group is workers who were working at $t = 0$, and did not separate due to their plant closing down or downsizing between $t = 0$ and $t = 1$. Hence, the control group includes both stayers and other separators. "Other separators" is a mixture of workers laid off for cause, workers temporarily leaving the labour force, e.g. due to bad health or to take more education, and voluntary quits such as ordinary job-to-job mobility.

In order to explore heterogeneity in the displacement effects, we expand equation (2) by including dummies for different displacement categories, cf. equation (3) below, and interactions between the displacement dummies and variables in the X and Z vectors. Next, we explore business cycle effects by varying the base year. The number of displacement dummies included before and after the displacement incident is then adjusted to fit the longest time span possible.

6 Selection issues

To what extent displacement, as defined in our analysis, is really exogenous, is obviously a key issue. Separations which result from plants closing down or downsizing is likely to be *close* to exogenous job losses since it is the result of an operational response of the employer to some exogenous shock. Individual worker characteristics are unlikely to be major determinants of plant shut downs or large scale employment reductions. We do acknowledge, however, that none of our displacement categories can be though as a generated by purely randomized experiments. There are two main reasons for this. First, there is selection of plants into exiting plants and downsizing plants. Such plants will be concentrated in industries, occupations and local labour markets experiencing reduced labour demand. This again is likely to affect the future employment conditions of the workers of these plants since their human capital is specific to troubled sectors or occupations. These workers have a high probability of becoming displaced, and as such they constitute a group for which the consequences of displacement is particularly policy relevant. It is, however, critical to compare their labour market outcome after displacement with non-displaced workers having similar characteristics. We hope to achieve this by including a rich set of control variables in the regressions. In addition we estimate the regressions with individual fixed effects. This means that we can control for non-time-varying unobserved heterogeneity between individuals.

A second selection issue is related to what happens within plants during a downsizing period. Downsizing-plant-separators and early-leavers may be a non-random sample of the plants' employees. Troubled plants have an obvious incentive to get rid of less productive workers, or more precisely workers that receive high compensation relative to their productivity. This may cause us to overestimate the cost of displacement. On the other hand, workers with relatively better external market opportunities and lower proportion of firm-specific human capital may be more likely to quit when their employment relationship becomes uncertain. These semi-voluntary quitters cannot be distinguished from the displaced workers, and this may cause us to underestimate the cost of displacement. Thus, the direction of the overall bias is ambiguous. Since a plant closing is often preceded by a period of significant downsizing this has ramifications also for the exit-layoffs. If workers leaving during a downsizing period is a selected sample, then workers who stay until the end will also be a selected group.[16] In order to explore possible differences between the three displacement categories[17], we estimate a model where the displacement effect is allowed to differ between the groups, i.e.

$$\begin{aligned} Y_{it} &= \mathbf{X}_{it}\beta + Z_{it}\gamma + \sum_{j=-2}^{8} EXIT_{it-j}\lambda_j \\ &\quad + \sum_{j=-2}^{8} EARLY_{it-j}\mu_j + \sum_{j=-2}^{8} DOWN_{it-j}\nu_j + \tau_t + \alpha_i + \epsilon_{it} \end{aligned} \tag{3}$$

where $EXIT_{it-j}$, $EARLY_{it-j}$ and $DOWN_{it-j}$ are dummy variables indicating whether a worker was displaced due to plant closure, separated from an exiting plant in the period before the closure or separated from downsizing plant. The dependent variable and the other covariates are identical to those in equation (2). We estimate the equation both with and without fixed effects (α_i).

7 Descriptive evidence

Figure 2A describes the share of employed workers among displaced workers, stayers and non-displaced workers from $t-3$ to $t+7$.[18] Clearly, the effect of displacement seems much stronger when comparing displaced workers to

[16] Lengermann et al. (2002) study the employment flows from plants prior to the plant closing down. They find important differences between the quality-composition of workers who leave the plant before it closes down and those who stay until end. Cf. also Hamermesh and Pfann (2001).

[17] Workers re-employment wages between different separation categories might also differ if market infers that workers in different displacement categories are off different ability. See Gibbons and Katz (1991).

[18] A worker is defined as employed if working full time for at least part of the year. All workers were full time employed in our base year 1991. Non-displaced workers comprise both stayers and non-displaced separators.

stayers than when comparing them to all non-displaced.[19] Note also that stayers have a better employment history than displaced workers prior to displacement. This suggests that the stayers is a selected sample of workers and not a valid control group. In the following analysis we use all the non-displaced workers as a control group for displaced workers.

Figure 3A describes the share of employed workers in the years following and preceding displacement for the three different categories of displaced workers. We find that exit-layoffs seem to have a higher probability of being re-employed in the short run as compared to the two other displacement categories, but a lower probability in the long run. Early leavers have the lowest employment rate in the short run, but the highest employment rate in the long run.

In Figure 2B and 3B the outcome variable is average annual earnings. Again, we find differences between the three groups, but somewhat surprisingly displaced workers do better than the non-displaced workers prior to displacement, while stayers are at the bottom of the earnings distribution. Note, however, that these findings are not robust to changes in the base year, cf. Figure 5A and 5B. We will return to this issue towards the end of our analysis when discussing business cycle effects.

There is a clear "dip" in earnings after displacement, lasting for about four years. There is, however, no evidence suggesting that the earnings of the displaced workers start to decrease before the displacement occurs. This will change in the regression analysis below, when we condition on worker characteristics. Then we find results more in line with the previous literature also on this point.

Table 3 give numbers for the employment status of workers one and seven years after separation.[20] From the upper part of the table we see that 81 per-

[19] Cf. e.g. Jacobson et al. (1993) for a study that uses only stayers as comparison group.

[20] More precisely in May 1992 and November 1998 for workers separating between May 1991 and May 1992.

cent of displaced workers are reemployed within one year.[21] For workers who are displaced because their plant closes down, the reemployment rate is as high as 88 percent. As noticed in Figure 3A, early leavers, i.e. workers separating from plants that will exit in the near future and workers from downsizing plants are worse off. 59 and 77 percent of these workers, respectively, are re-employed within one year. This lower reemployment rate could be because they hope to be recalled and therefore are more reluctant to accept new jobs. It could also be due to selection, i.e. workers with low productivity being laid off first. The last column shows that among other workers, i.e. the non-displaced, 3 percent are not working one year later.

The lower part of Table 3 focuses on long term effects. We see that reemployment of workers displaced from plants that close down happens mainly in the first year after displacement. Seven years after displacement, employment has actually fallen by eleven percentage points, to 76 percent. This is also evident from Figure 2A, showing that employment peaks four years after displacement. Interestingly, Table 3 shows that employment among early leavers seven years after displacement is higher than employment among exit layoffs. Downsizing separators are still in between the two other groups. The improved position of early-leavers and downsizing plant separators is consistent with their higher non-employment rate one year after displacement being due to a hope for recall rather than selection. Such an explanation is plausible as labour unions demand that workers are laid off according to seniority. This makes it difficult for troubled firms to systematically lay off "lemons". We also see that laid off workers do have a realistic hope of being recalled. As many as 20 percent of workers laid of from plants that do not exit in the meantime are back at the same plant five years after the displacement incident. About 2 percent of the displaced workers are unemployed seven years later and about 18 percent is outside the labour force. This compares

[21] If separations are equally distributed throughout the year, the average worker was displaced six months ago. Some workers, obviously, will have been displaced quite recently.

to 2 percent unemployed and 8 percent out of the labour force among other workers, suggesting that the long term effect of displacement is mainly a significantly higher probability of permanent job loss. 31 percent of the displaced workers are still working in the same 2-digit industry. 9 percent are in a different 2 digit manufacturing industry while 25 percent are working in the private service sector and 5 percent are in the public sector. The relative share of employed workers changing industry is far higher among displaced workers than among other workers suggesting that displacement is a forceful vehicle for industry restructuring.

8 Regression results

The descriptive evidence discussed above do not control for observable differences between displaced and non-displaced workers that may be correlated with employment and earnings. In this section such control variables is taken into account by analyzing the costs of displacement within a regression framework. We first look at the effect of displacement on the probability of leaving the labor force. Then we analyze the effect of displacement on employment and earnings contingent on being in the labour force.

8.1 The effect of displacement on the probability of leaving the labour force

Table 4 reports probit estimates for how displacement affects the probability of being permanently out of the labour force already one year after displacement. From Model 1 we see that displacement significantly increases this probability. Worker's tenure and schooling decreases this probability, but very slightly. Model 2 allows the displacement effect vary by type of displacement. We see that workers who are displaced in plant closing down, or from downsizing plant, are more likely to be pushed permanently outside labour force after displacement than workers who separated from dying plants in the period before the closure occurred.

Table 5 reports probit estimates for how displacement affects the probability of being out of the labour force seven years after displacement. These workers include both the ones who were pushed permanently outside labour force after the initial separation, and those who have been in labour force between t and t+7. The latter group might consist of workers who were re-employed but were not able to find good job matches after the initial displacement. Results indicate that displaced workers have significantly higher probability of being outside labour force seven years after the displacement occurred. Workers with more schooling, and tenure, and those who were displaced from big plants are less likely to be outside labour force. Model 2 shows that workers displaced in plant closing down or from downsizing plants are more likely to be outside labour force in the seventh year after displacement than early-leavers from dying plants.

8.2 Average effects of displacement on employment and earnings for workers in the labour force

Table 6A reports of the effect of displacement happening between May 1991 and May 1992 on months of full time employment in the years 1988 through 1998. The OLS specification in the first column control for workers' age, age squared, years of schooling, years of tenure in the base year, whether married or not in the base year, plant size in the base year measured by number of employees, size of the regional labour market in the base year measured by number of employees, the regional unemployment rate and dummies for region, two digit ISIC industry and year. The specification does not control for displacement happening after May 1992. Hence, to the extent that the treatment group experience more displacements in the years 1992 to 1998, it will be considered a causal effect of the displacement in 1991.

Note that if displacements happen evenly throughout the year, the "average" displacement will happen in November 1991. Since the average displacement date is towards the end of the year, we will expect to see at least as strong effect in the calendar year 1992 as in 1991. The effect for the calendar year 1992 is picked up by the dummy variable "Displaced at $t-1$" (D_{t-1}). The coefficients on the variable D_t, represents the effect in 1991. Given that all job relationships last at least until May that year it will pick up both the effect of working for a troubled firm at the verge of closure or downsizing, and some immediate effects of displacement. The coefficients on the variables D_{t+1}, D_{t+2} and D_{t+3} are pure pre-displacement effects. The coefficients on the variables D_{t-2} to D_{t-7} are long time effects of having been displaced 1-2 years ago and up to 6-7 years ago.

The OLS estimates indicate a negative and significant employment effect for all years before and after displacement.[22] This is consistent with findings from previous studies. Workers who are displaced work on average 2.0 months less in the following year as compared to similar non-displaced workers. It is only in the first 3 years after displacement that the average employment reduction is more than one month per year. Seven year after displacement, displaced workers work on average 0.2 months less than the non-displaced workers. Three years before the displacement, the effect is negative 0.1 months.

If there are more low productivity workers among the displaced workers than in the control group, the OLS results will be biased and overstate the negative effect of displacement. One way to correct for this potential selection bias, is to include individual specific fixed effects controlling for unobserved worker characteristics. Doing this we see that the effects of displacement becomes slightly smaller. The first year effect is reduced from 2.0 months to 1.9 month, and the seventh year effect is reduced from 0.2 months to

[22] A large share of the workers will work 12 or 0 months, hence our dependent variable is limited and not normally distributed. Given our large sample, this should not invalidate the OLS results, but as a robustness check, we have also used a Tobit specification. The qualitative results are the same.

essentially zero. Note, that the fixed effects specification simply measures the effect relative to employment three years before the displacement incident as this displacement dummy is removed in order to avoid perfect colinearity. The OLS specification without fixed effects suggests that there is an early negative effect of displacement already at that time, of about 0.1 months. This corresponds to the difference between the OLS and the fixed effects results. Without tracing the workers' employment histories further back in time, we cannot identify whether this coefficient reflects selection or the effect of working for a troubled firm. Remember that Jacobson et al. (1993) report that the effect of displacements start to show up in their data about three years prior to displacement. In any case, the pre-displacement effects in the fixed effects specification should be interpreted as "troubled firm" effects. These effects are slightly more than 0.1 month. Hence, the pre-displacement effects are very small in magnitude, although fairly precisely estimated.

Having examined the effect of displacement on employment, we look in Table 6B at the effect on earnings. We find evidence of a negative and significant earnings effects. In the year immediately after job loss displaced workers' earnings are reduced by 5 percent according to the OLS specification and by 2 percent according to the fixed effects specification. The effect decreases slowly, and is according to the OLS specification 2 percent seven year after displacement. According to the fixed effects specification there is hardly any earnings effect at all in the long run. The pre-displacement effect on earnings is roughly constant in the OLS specification, around 3 percent, and consequently zero in the fixed effects specification. This suggest that the pre-displacement earnings difference between the two groups are due to selection, rather than working for a troubled firm. The lack of an earnings effect associated with working for a troubled firm make sense as the estimated average employment effect in the preceding years is at most one week, and the workers will receive unemployment benefits close to their actual wage.

8.3 Effects of displacement by displacement category

Our treatment group consists of three different sub categories, exit-layoffs, early-leavers and downsizing plant separators. Various potential selection biases could pertain to these groups, as explained in section 6. In order to investigate this, we allow the displacement effect to differ between the groups, as described by equation (3).

The OLS results in Table 7A confirm negative employment effects for all displacement categories. The short run negative effect is, however, weaker for workers that were displaced by plant exit than for the other two categories. Exit-layoffs work on average 1.3 months less in the year immediately following displacement as compared to workers that were not displaced. Workers who left exiting plants in the period before it closed down, work on average 4.0 months less in the year immediately following displacement, and downsizing-plant-separators work on average 2.3 months less. This could indicate that workers who stay on until the end are indeed more productive than those laid off earlier, but the differences could as well reflect differences in search behavior as discussed previously. The long run effects are quite similar across the different groups, and this points to differences in search behavior as the more likely explanation for differences in the short run. The FE results reported in the right hand side of Table 7A is largely in accordance with the OLS results although the magnitude is somewhat smaller.

Table 7B reports the earnings regressions. Looking at the OLS results we do not find any systematic difference between the three groups with respect to earnings after displacement. There are, however, differences in post-displacement earnings making the fixed effects specification look a bit different. When controlling for earnings differences present at $t-3$, we see that early leavers and to some extent downsizing plant separators experience a significantly higher earnings loss in the short term than exit-layoffs. In the long run none of the groups seem to face any reductions in earnings. This is consistent with the employment effects.

To sum up, we find that the average effect of displacement on workers employment and earnings are negative and significant, but overall fairly modest. There are some short term differences between those displaced by plant exit and those displaced from troubled firms. These differences may have to do with the latter group hoping to be recalled and therefore searching less intensely for a new job.

8.4 Heterogeneity in the effects of displacement

In section 8.2, we found significant, but fairly modest average effects of displacement. It is not obvious, however, that the effect of displacement is equally distributed across workers with different characteristics. For example, if the earnings loss for displaced workers are explained by the loss in firm-specific human capital, workers with long pre-displacement job tenure should suffer more severe reductions in their earnings than workers with short pre-displacement job tenure. If, on the other hand, the earnings and employment reduction reflects that workers in exiting and downsizing firms are situated in labour markets which are doing badly, the losses should differ according to the characteristics of the local labour markets. Heterogeneity in the effects of displacement is an important policy issue. If certain types of workers, displaced from certain types of firms in certain types of labour markets, are more likely to suffer severe losses after displacement, we may target employment policies directly towards these groups.

In order to investigate potential heterogeneity in the displacement effects, we interact the displacement dummies with various pre-displacement worker and plants characteristics. We use a high/low dichotomy, e.g. old vs. young workers, as reported in Table 8A and 8B. Old workers are defined as workers between 45 and 55 years at the time of the displacement incident while young workers are those between 25 and 44 years. Conventional wisdom suggests that it is more difficult for old workers than for young workers to find new employment. There is little support for this view in our data. There is no short term difference between young and old workers, and only a very small difference, about 0.15 months, seven years after displacement. Note however, that workers that have been permanently pushed out of the labour force are not included in the sample. Table 8B reports the effect on earnings broken down by age. Here the results suggest that old workers experience a somewhat larger wage loss, particularly in the long run.

As mentioned above, one reason why old workers face larger problems after a displacement incident may be that they have more firm specific human capital than young workers. This is explored in Table 9A and 9B. Table 9A reports the effects of displacement on months of full time employment by pre-displacement job tenure. Low tenure is defined as tenure less than three years. We find a picture that resembles the age effect. There is no short term difference between high and low tenured workers, but high tenured workers are employed about 0.5 months less than low tenured workers seven years after displacement. Actually, it is only high tenured workers that seem to face any negative consequences in the long run.

Table 9B reports the effects of displacement on annual earnings. According to the fixed effects specification the difference between high and low tenured workers is very small. The OLS specification, on the other hand, suggests that workers with long tenure have about a two percentage points lower earnings.

In Table 10A and 10B we investigate the effects of displacement by educational length. Highly educated workers should have more general human capital and be more flexible in the labour market. Our data clearly confirm this hypothesis, both with respect to earnings, and employment. Workers with 10 or less years of schooling work about 2.5 months less than similar non-displaced workers in first years after displacement and about 0.2 months less seven years after displacement. Workers with more than 10 years of schooling work about 1.5 months less than similar non-displaced workers in first years after displacement and do not appear to have any long term employment reduction. With respect to earnings, workers with 10 or less years of schooling face an average earnings reduction around 6-9[23] percent in first years after displacement and an earnings reduction around 5 percent seven years after displacement. Workers with more than 10 years of schooling face an earnings reduction of 0-5 percent in the short run, and they do not seem to face any earnings reduction in the long run. This is consistent with the findings by Stevens (1997) and Kletzer (1989). They argue that those employed in white collar jobs have more transferable human capital and so may loose less from displacement and recover more rapidly.

Table 11A and 11B reports the effects of displacement by plant size. Our hypothesis is that large plants will be both in a better position to help their workers transfer into new jobs and under more pressure from special interest groups. Our data clearly supports this hypothesis. Table 11A shows that workers displaced from plants with more than 100 employees are employed two months more in the first year after displacement as compared to workers from smaller plants. The difference disappears gradually over the next seven years. The earnings effect goes in the same direction. Workers from plants with less than 100 employees face a larger earnings reduction both in the short and in long run.

Finding a suitable new job is easier in a large than in a small labour market. Table 12A and 12B report the effects of displacement by labour market size, and we see that the hypothesis is supported by the data although the effect is not particularly strong. In the short run workers displaced in labour markets with a population smaller than 50 000 are employed about 0.4 months less than workers displaced in larger labour markets. The difference disappears gradually. With respect to earnings, the difference is only noticeable in the fixed effects specification.

Our final analysis in this section looks at whether there are differences in the effects of displacement between workers displaced from "sunset indus-

[23] Depending on whether one looks at the OLS or the fixed effects results.

tries" and other industries. "Sunset industries" are defined as industries at the five digit level with 15 percent or more decline in relative employment between 1980 and 1990. The results are reported in Table 13A and 13B. As expected, workers displaced from sunset industries face somewhat larger problems than other displaced workers. On average workers displaced from sunset industries are unemployed for about 0.5 month more during the first year after displacement, and about 0.1 months more per year in the long run. There is a corresponding difference in earnings.

8.5 Varying the base year

So far, we have only analyzed effects of displacements happening in 1991. By redoing the main analysis on displacements happening in other years, we can check how robust our results are with respect to changes in the sample and the time period analyzed. We are in particular interested in seeing whether there are systematic differences in the effects of displacement over the business cycle.

Figure 4A and 4B show effects of displacement on employment for displacements happening in each of the years the 1988 through 1994. We see that the shape is pretty similar across different years, although the level varies a bit. Figure 5A and 5B have earnings as the outcome variable. It appears as if workers displaced in 1988 and 1989, the very beginning of the economic downturn, are lower paid than non-displaced workers before their displacement, and that the earnings loss is particularly large and long lasting for these workers. Further into the downturn, displaced workers seem much more similar to non-displaced workers, cf. the results in our main analysis using 1991 as base year. There are, however, also year to year changes in the earnings curves that are hard to relate to changes in the business cycles. It looks, e.g. as if the first year earnings loss is particularly small in 1991.

9 Conclusions

We have examined the impact of displacement on workers' employment and earnings using a large panel with linked employer-employee data from Norway. We have focused on workers displaced by plant closings and workers separating from downsizing plants. We find that 88 percent of workers who are displaced because their plant closes down are re-employed within one year after the separation occurs. Early leavers, i.e. workers separating from plants that will exit in the near future and workers from downsizing plants are somewhat worse off. Reemployment of workers displaced from plants that close down happens mainly in the first year after displacement. Seven years after displacement, employment has actually fallen to about 76 percent. Employment among early leavers and downsizing separators seven years after displacement is higher than employment among exit layoffs. This is consistent with the higher unemployment rate among early leavers and downsizing separators one year after displacement being due to a hope for recall rather than selection. As many as 20 percent of workers laid of from plants that do not exit in the meantime are back at the same plant five years after the displacement incident. 2.3 percent of the displaced workers are unemployed seven years later and 17.7 percent is outside the labour force. This compares to 1.7 percent unemployed and 7.7 percent out of the labour force among other workers, suggesting that displacement strongly increases the probability of permanent job loss. The relative share of employed workers changing industry is far higher among displaced workers than among other workers suggesting that displacement is a forceful vehicle for industry restructuring. A significant share of workers displaced from the manufacturing industry find a new job in the service sector.

Using a regression framework, we find that workers who are displaced and not pushed out of the labour force work on average 2 months less in the following year as compared to similar non-displaced workers. It is only in the first 3 years after displacement that the average employment reduction is more than one month per year. Seven year after displacement, displaced workers work on average only a few days less than the non-displaced workers per year. In the years prior to displacement, future displaced workers look very much like the non-displaced group. This finding, however, is not robust to changing the base year of the analysis. It appears that early in an economic downturn, displaced workers are more "marginal" than non-displaced workers. When analyzing earnings, we find that in the year immediately after the job loss displaced workers' earnings are reduced by 2-5 percent. The effect decreases slowly, and is about 1-2 percent seven years after displacement.

When investigating heterogeneity in the effects of displacement, we find that workers with 10 or less years of schooling perform worse than workers with more education. This is consistent with educated workers having more general human capital and therefore being more flexible in the labour market. We also find that workers displaced from small plants are more vulnerable. When looking at young vs. old workers, workers with high and low tenure, workers displaced from small and large labour markets and workers displaced from sunset industries vs. other industries we find surprisingly small differences, although the differences we find tend to go in the expected direction.

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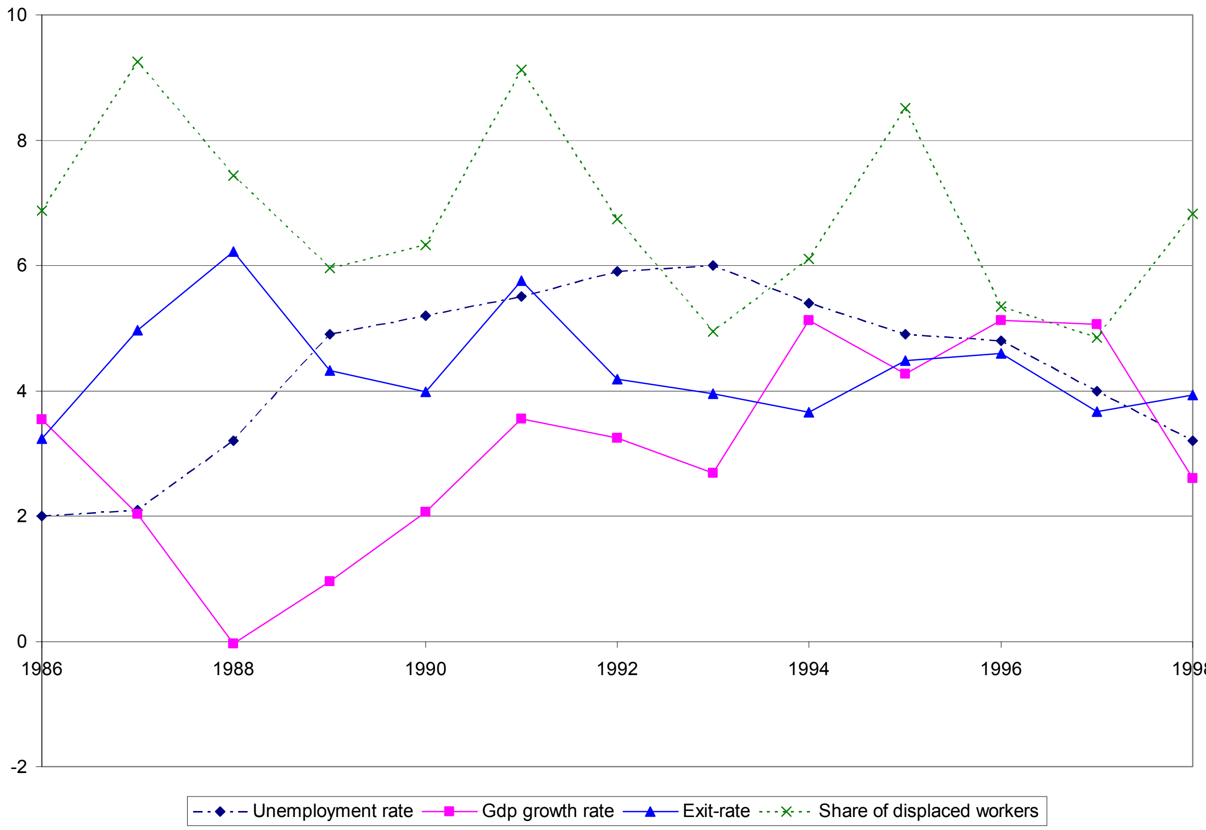
APPENDIX TO SECTION IV

Figure 1 Business cycle indicators, plant exit rate and share of displaced workers in Norway 1986-1998

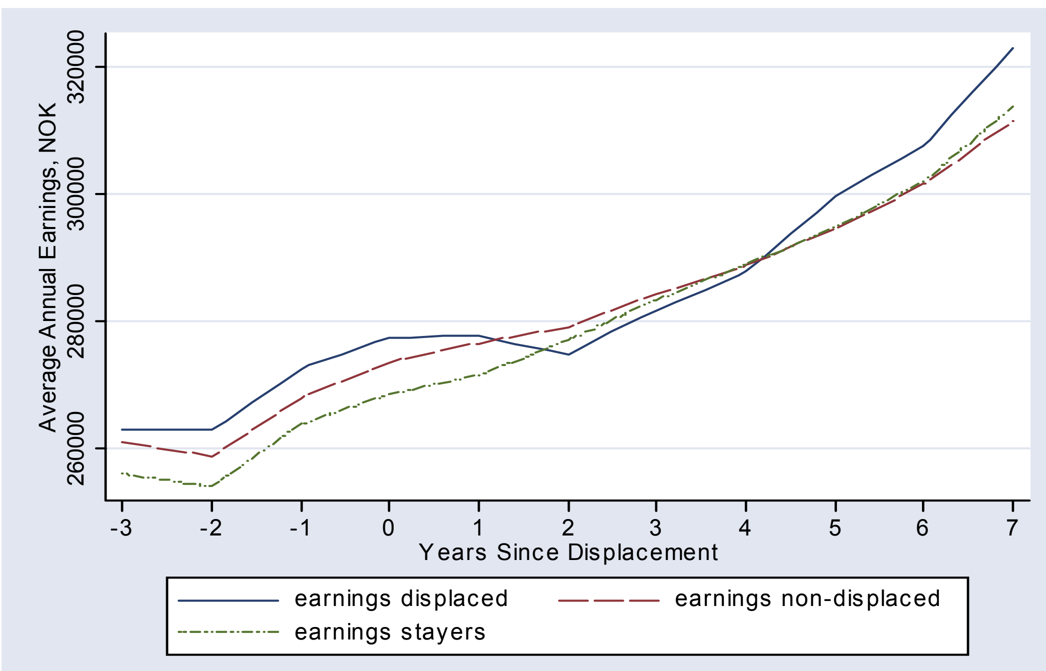


Cf. subtext to Table 1 for details.

Figure 2A The effect of displacement on *employment*

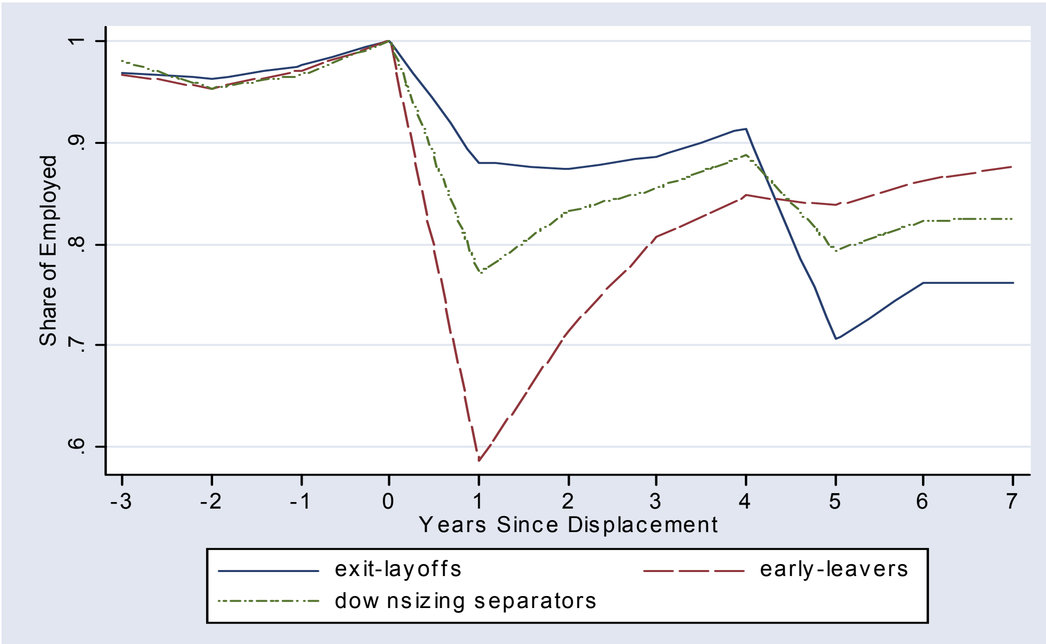
The sample consists of 25-55 year old male workers full time employed in manufacturing in 1991 (year 0), who were in the labour force and not displaced from their jobs in the previous three years.

Figure 2B The effect of displacement on *earnings*



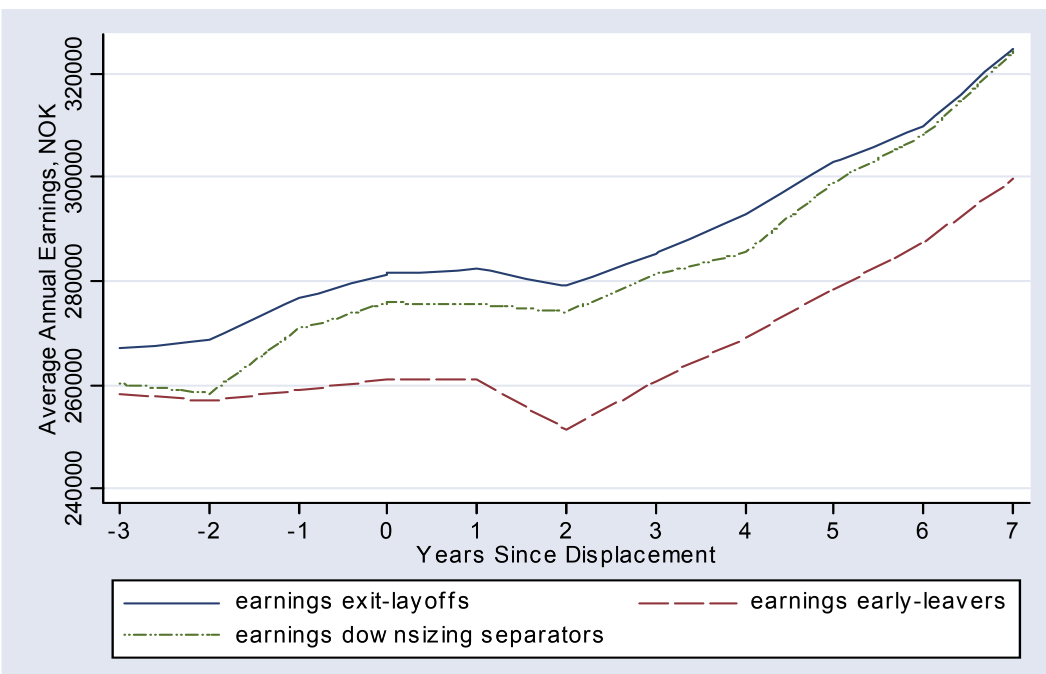
The sample consists of 25-55 year old male workers full time employed in manufacturing in 1991 (year 0), who were in the labour force and not displaced from their jobs in the previous three years.

Figure 3A The effect of displacement on *employment* by displacement type



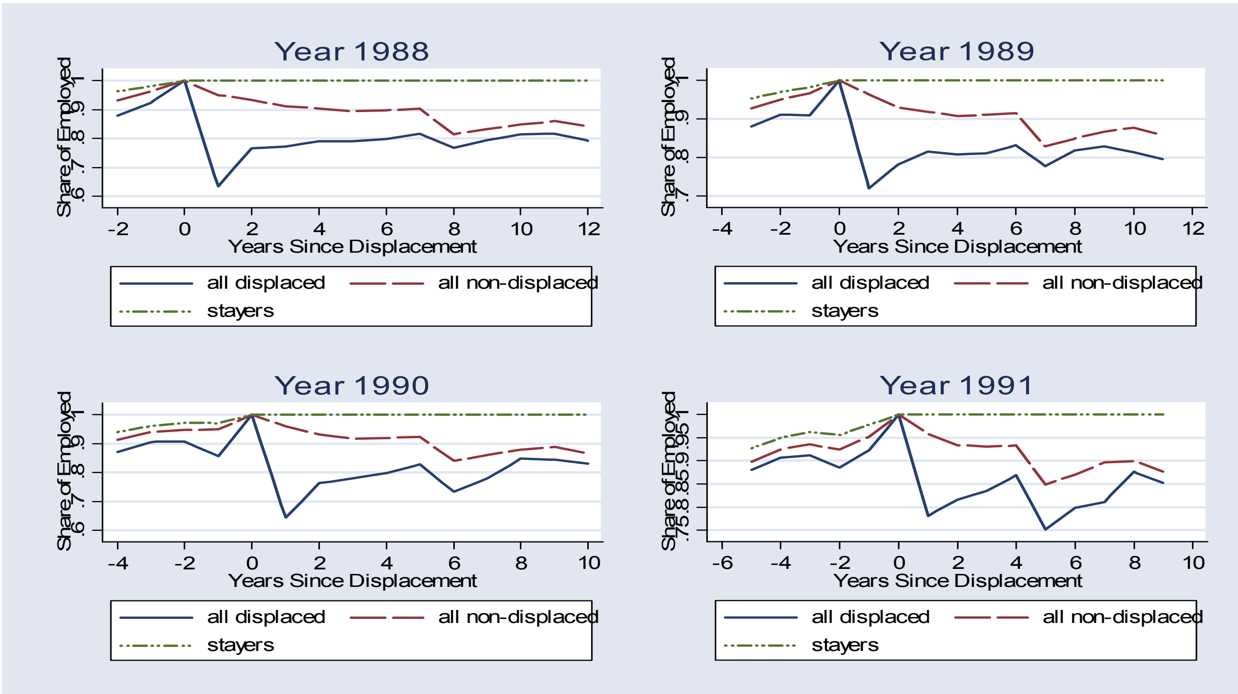
The sample consists of 25-55 year old male workers full time employed in manufacturing in 1991 (year 0), who were in the labour force and not displaced from their jobs in the previous three years.

Figure 3B The effect of displacement on *earnings* by displacement type



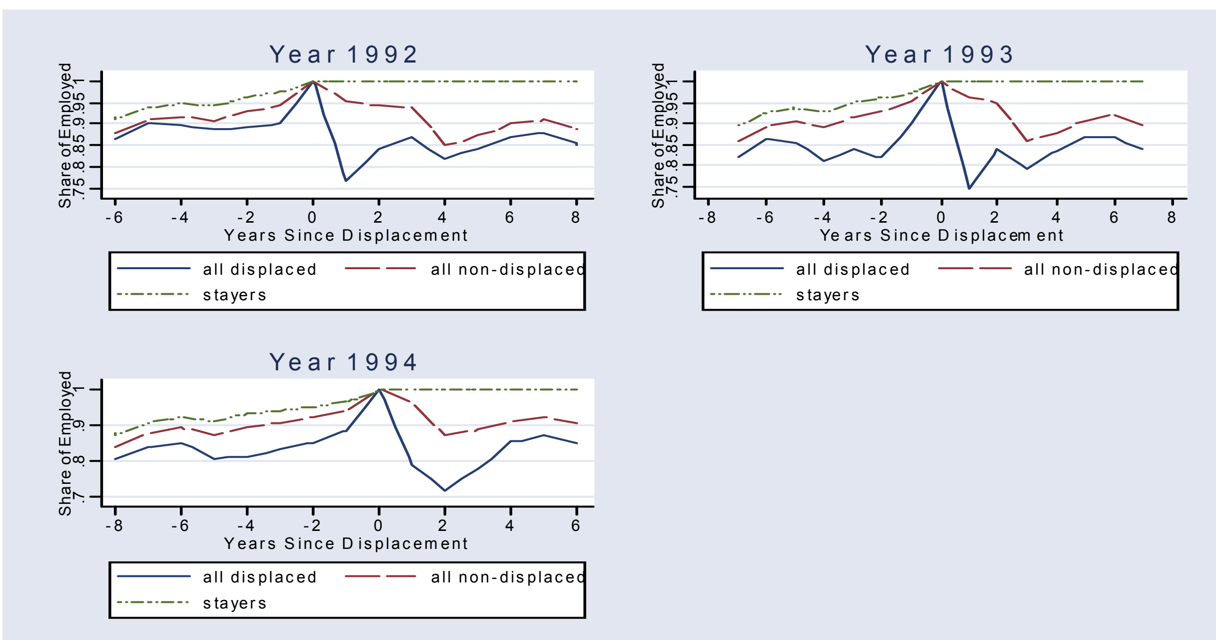
The sample consists of 25-55 year old male workers full time employed in manufacturing in 1991 (year 0), who were in the labour force and not displaced from their jobs in the previous three years.

Figure 4A Share of employed by displacement year (1988-1991)



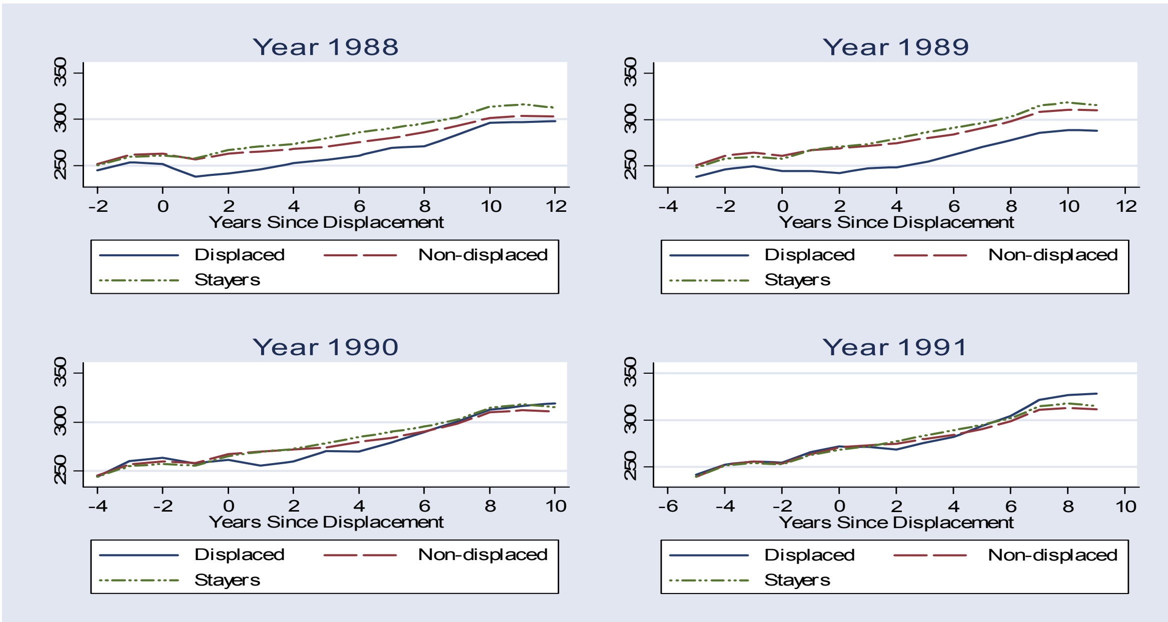
The sample consists of 25-55 year old male workers full time employed in manufacturing in year 0, who were not displaced from their jobs in the previous two years.

Figure 4B Share of employed by displacement year (1992-1994)



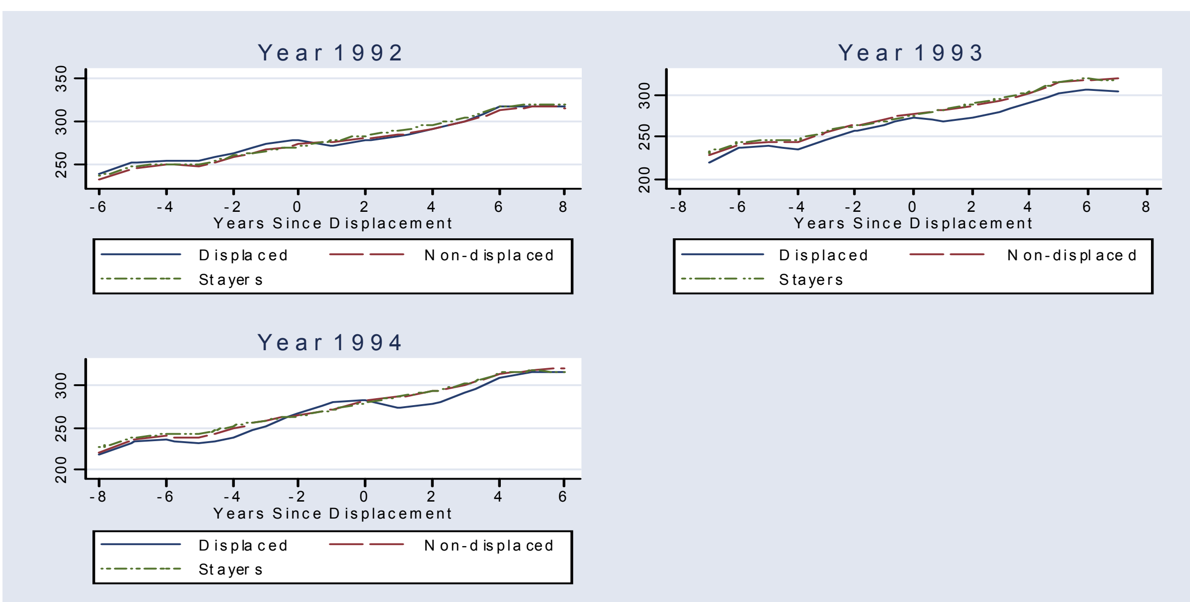
The sample consists of 25-55 year old male workers full time employed in manufacturing in year 0, who were not displaced from their jobs in the previous two years.

Figure 5A Average annual earnings of displaced, non-displaced and stayers by displacement year (1988-1991)



The sample consists of 25-55 year old male workers full time employed in manufacturing in year 0, who were not displaced from their jobs in the previous two years. Average annual earnings in thousand NOK.

Figure 5B Average annual earnings of displaced, non-displaced and stayers by displacement year (1992-1994)



The sample consists of 25-55 year old male workers full time employed in manufacturing in year 0, who were not displaced from their jobs in the previous two years. Average annual earnings in thousand NOK.

Table 1 **Business cycle indicators and the share of full time workers displaced from Norwegian manufacturing plants 1986-1998**

Year	Unemployment rate	Change in the unemployment rate	Growth rate	Plant exit rate	Share of full time workers displaced	*Share of full time workers displaced due to plant exits*	*Share of full time workers displaced from plants exiting next period (early-leavers)*	*Share of full time workers displaced from downsizing-plant*
1986	2.0	-0.60	3.54	3.23	6.87	1.98	1.26	3.63
1987	2.1	0.10	2.03	4.96	9.25	3.35	1.37	4.52
1988	3.2	1.10	-0.04	6.22	7.43	2.26	0.85	4.31
1989	4.9	1.70	0.95	4.32	5.96	1.55	0.81	3.61
1990	5.2	0.30	2.06	3.99	6.33	2.10	0.86	3.37
1991	5.5	0.30	3.55	5.75	9.12	4.03	0.62	4.47
1992	5.9	0.40	3.25	4.18	6.74	2.61	0.59	3.54
1993	6.0	0.10	2.69	3.95	4.94	1.85	0.46	2.64
1994	5.4	-0.60	5.12	3.66	6.11	1.38	1.03	3.70
1995	4.9	-0.50	4.27	4.48	8.52	3.74	0.74	4.04
1996	4.8	-0.10	5.12	4.60	5.35	2.22	0.53	2.60
1997	4.0	-0.80	5.06	3.67	4.85	1.43	1.03	2.39
1998	3.2	-0.80	2.60	3.93	6.83	1.76	2.02	3.04

The growth rate is the percent change in GDP from year *t*-1 to *t*. A plant is defined as an exiting plant if it is present at *t*, but absent at *t*+1 and *t*+2 (and later if that is possible to check). The displacement rate is the share of workers who were displaced from their jobs between *t* and *t*+1 among workers who were working full time in plants with at least 5 employees in period *t*. The displaced workers can be divided into three sub categories: Workers who separated between *t* and *t*+1 from plants that exited between *t* and *t*+1 (exit-layoffs), workers who separated between *t* and *t*+1 from plants that exited between *t*+1 and *t*+2 (early-leavers), and workers who separated between *t* and *t*+1 from plants that reduced their size by more than 30% between *t* and *t*+1 (downsizing plant separators).

Table 2A Sample means of selected pre-displacement *worker characteristics* by displacement status

	All workers	All displaced workers	*Exit-layoffs*	*Early leavers*	*Downsizing plant separators*	All non-displaced workers	*Stayers*	*Separators*
Age at *t*	39.21	38.83	39.04	38.35	38.70	39.24	39.42	36.98
Education at *t*	10.75	11.13	11.29	10.89	11.02	10.72	10.69	11.11
Tenure at *t*	7.36	6.08	6.61	5.78	5.65	7.48	7.67	5.14
Married at *t*	0.66	0.64	0.67	0.63	0.62	0.66	0.66	0.58
Earnings at *t*-1	237238	240205	243684	225939	238897	236975	237352	232280
Earnings at *t*-3	200823	202338	205363	198510	200087	200689	200837	198839
No. of observations	103240	8427	3756	537	4134	94813	87759	7054

Displacements happened between May 1991 and May 1992. The sample consists of 25-55 year old male workers full time employed in manufacturing in 1991 (year *t*), who were in the labour force and not displaced from their jobs in the previous three years.

Table 2B Sample means of selected pre-displacement *plant characteristics* by plant categories

	All plants	Exiting plants	Downsizing plants	Other plants
Employment at *t*	41.90	30.88	36.67	43.08
Employment at *t*-1	41.67	31.30	36.68	42.79
Average worker age at *t*	39.72	39.34	39.46	39.77
Average tenure at *t*	5.52	3.65	4.59	5.73
Average schooling at *t*	10.29	10.39	10.18	10.30
Share of female at *t*	0.28	0.26	0.28	0.28
Share of married at *t*	0.59	0.57	0.57	0.59
Plant age at *t*	19.34	15.86	17.77	19.56
Employment growth, *t-1* to *t*	0.17	0.14	0.21	0.17
Employment growth, *t* to *t+1*	0.00	-1.00	-0.51	0.05
No. of observations	6330	333	531	5466

The sample consists of manufacturing plants with more than five employees in 1991 (year *t*). The plants are categorized based on what happens with employment from year *t* to *t+1*. Plant age is censored at 26.

Table 3 **Percentage of workers employed one and seven years after displacement by displacement type**

One year after	All displaced	*Exit -Layoffs*	*Early-Leavers*	*Downsizing separators*	Other workers
Employed	80.79	87.99	58.66	77.12	97.22
same plant	0.00	0.00	0.00	0.00	92.56
same industry, different plant	43.69	63.79	30.17	27.19	1.92
other manufacturing industry	11.55	4.10	8.01	18.77	0.57
private service	23.51	19.12	17.88	28.23	1.86
public service	2.04	0.99	2.61	2.93	0.31
Not-employed	19.21	12.01	41.34	22.88	2.78
Registered as unemployed	14.87	8.63	32.40	18.26	2.00
temporarily outside the labour force	3.74	2.80	8.57	3.97	0.67
permanently outside the labour force	0.61	0.59	0.37	0.65	0.11

Seven years after	All displaced	*Exit -Layoffs*	*Early-Leavers*	*Downsizing separators*	Other workers
Employed	80.00	76.20	87.71	82.46	90.65
same plant	9.99	0.00	0.00	20.37	59.95
same industry, different plant	30.82	44.54	30.35	18.41	12.03
other manufacturing industry	8.98	7.29	14.53	9.80	3.48
private service	25.39	18.21	37.62	30.33	13.56
public service	4.82	6.15	5.21	3.56	1.63
Not-employed	20.00	23.80	12.29	17.54	9.35
Registered as unemployed	2.28	2.10	2.42	2.42	1.66
outside the labour force	17.72	21.70	9.87	15.12	7.70
No. of observations	8427	3756	537	4134	94813

Displacements happened between May 1991 and May 1992. The sample consists of 25-55 year old male workers full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years. Permanently outside the labour force means outside the labour force at least until the seventh year after displacement.

Table 4 The effect of displacement on the probability of being *permanently* out of the labour force in *the first year* after displacement

	Model 1		Model 2	
Age ∈ {35, 44}	0.000	(0.000)	0.000	(0.000)
Age ≥ 45	0.000	(0.000)	0.000	(0.000)
Years of schooling	-0.001	(0.004)	-0.001	(0.004)
Tenure when displaced	-0.002	(0.002)	-0.002	(0.002)
Marital status when displaced	0.000	(0.000)	0.000	(0.000)
Plant size when displaced	-0.000	(0.003)	-0.000	(0.000)
Size of the regional labour market when displaced	0.000	(0.000)	0.000	(0.000)
Regional rate of unemployment	-0.029	(0.020)	-0.028	(0.019)
Displaced	0.004	(0.001)		
Type of displacement:				
Exit-layoff			0.005	(0.001)
Early-leaver			0.002	(0.002)
Downsizing plant separator			0.005	(0.001)
No. of observations	103240		103240	
Pseudo R-squared	0.0709		0.0713	

Probit estimates. The sample year is 1992. Displacements happened between May 1991 and May 1992.The sample consists of 25-55 year old male workers full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years. The coefficients are marginal effects, i.e. d[P(Y=1)]/dX. Permanently outside the labour force means outside the labour force at least until the seventh year after displacement. Years of schooling, tenure, plant size and regiol labour market size variables are divided by 100. Robust standard errors are in parenthesis.

Table 5 The effect of displacement on the probability of being out of the labour force in *the seventh year* after displacement

	Model 1		Model 2	
Age ∈ {35, 44}	-0.003	(0.003)	-0.003	(0.003)
Age ≥ 45	0.008	(0.003)	0.007	(0.003)
Years of schooling	-0.078	(0.041)	-0.078	(0.039)
Tenure when displaced	-0.055	(0.017)	-0.054	(0.017)
Marital status when displaced	-0.007	(0.002)	-0.007	(0.002)
Plant size when displaced	0.004	(0.014)	0.004	(0.000)
Size of the regional labour market when displaced	0.000	(0.000)	0.000	(0.000)
Regional rate of unemployment	0.117	(0.354)	0.148	(0.345)
Displaced	0.062	(0.004)		
Type of displacement:				
Exit-layoff			0.056	(0.006)
Early-leaver			0.033	(0.014)
Downsizing plant separator			0.075	(0.006)
No. of observations	103240		103240	
Pseudo R-squared	0.0518		0.0713	

Probit estimates. The sample year is 1998. Displacements happened between May 1991 and May 1992.The sample consists of 25-55 year old male workers full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years. The coefficients are marginal effects, i.e. d[P(Y=1)]/dX. Years of schooling, tenure, plant size and regiol labour market size variables are divided by 100. Robust standard errors are in parenthesis.

Table 6A The effect of displacement on *employment*

	OLS		FE	
Age	0.078	(0.004)	0.070	(0.003)
Age squared	-0.001	(0.000)	-0.001	(0.000)
Years of schooling	0.036	(0.002)		
Tenure when displaced	0.040	(0.001)		
Marital status when displaced	0.228	(0.009)		
Plant size when displaced	0.020	(0.001)		
Size of the regional labour market when displaced	0.000	(0.000)		
Regional rate of unemployment	-16.308	(0.672)	-19.395	(0.477)
Displaced at *t+3*	-0.131	(0.024)		
Displaced at *t*+2	-0.256	(0.027)	-0.127	(0.032)
Displaced at *t+1*	-0.276	(0.024)	-0.144	(0.032)
Displaced at *t*	-0.346	(0.015)	-0.212	(0.032)
Displaced at *t-1*	-2.020	(0.054)	-1.884	(0.032)
Displaced at *t-2*	-1.431	(0.050)	-1.294	(0.032)
Displaced at *t-3*	-1.128	(0.047)	-0.991	(0.032)
Displaced at *t-4*	-0.775	(0.043)	-0.638	(0.032)
Displaced at *t-5*	-0.612	(0.041)	-0.474	(0.032)
Displaced at *t-6*	-0.360	(0.035)	-0.223	(0.032)
Displaced at *t-7*	-0.155	(0.029)	-0.019	(0.032)
No. of observations	1038972		1038972	
R-squared	0.0465		0.0204	

The dependent variable is months of employment. Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The specification without individual fixed effects contains region and industry dummies. Both specifications contain time dummies. Robust standard errors are in parenthesis.

Table 6B The effect of displacement on *earnings*

	OLS		FE	
Age	0.041	(0.001)	0.054	(0.000)
Age squared	0.000	(0.000)	0.000	(0.000)
Years of schooling	0.059	(0.000)		
Tenure when displaced	0.002	(0.000)		
Marital status when displaced	0.083	(0.002)		
Plant size when displaced	0.006	(0.000)		
Size of the regional labour market when displaced	0.000	(0.000)		
Regional rate of unemployment	-1.732	(0.117)	-1.343	(0.055)
Displaced at *t+3*	-0.031	(0.004)		
Displaced at *t*+2	-0.032	(0.004)	-0.001	(0.004)
Displaced at *t+1*	-0.029	(0.004)	0.002	(0.004)
Displaced at *t*	-0.034	(0.004)	-0.004	(0.004)
Displaced at *t-1*	-0.053	(0.004)	-0.023	(0.004)
Displaced at *t-2*	-0.070	(0.005)	-0.040	(0.004)
Displaced at *t-3*	-0.062	(0.005	-0.032	(0.004)
Displaced at *t-4*	-0.062	(0.005)	-0.032	(0.004)
Displaced at *t-5*	-0.040	(0.005)	-0.010	(0.004)
Displaced at *t-6*	-0.039	(0.005)	-0.009	(0.004)
Displaced at *t-7*	-0.022	(0.005)	0.008	(0.004)
No. of observations	1038972		1038972	
R-squared	0.2640		0.0742	

The dependent variable is ln(annual earnings). Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The specification without individual fixed effects contains region and industry dummies. Both specifications contain time dummies. Robust standard errors are in parenthesis.

Table 7A The effect of displacement on *employment* by displacement type

	OLS						FE					
	Exit layoffs		Early leavers		Down-sizing separators		Exit layoffs		Early leavers		Down-sizing separators	
Displaced at *t*+3	-0.206	(0.039)	-0.038	(0.088)	-0.080	(0.032)						
Displaced at *t*+2	-0.290	(0.042)	-0.137	(0.101)	-0.242	(0.036)	-0.085	(0.048)	-0.097	(0.116)	-0.167	(0.044)
Displaced at *t*+1	-0.250	(0.034)	-0.163	(0.095)	-0.312	(0.035)	-0.042	(0.048)	-0.120	(0.116)	-0.234	(0.044)
Displaced at *t*	-0.294	(0.022)	-0.397	(0.064)	-0.382	(0.020)	-0.084	(0.048)	-0.352	(0.116)	-0.301	(0.044)
Displaced at *t*-1	-1.341	(0.072)	-4.035	(0.241)	-2.311	(0.079)	-1.129	(0.048)	-3.987	(0.116)	-2.227	(0.044)
Displaced at *t*-2	-1.153	(0.072)	-2.763	(0.230)	-1.480	(0.070)	-0.939	(0.048)	-2.715	(0.116)	-1.396	(0.044)
Displaced at *t*-3	-0.948	(0.068)	-1.772	(0.203)	-1.190	(0.067)	-0.734	(0.048)	-1.726	(0.116)	-1.105	(0.044)
Displaced at *t*-4	-0.648	(0.062)	-1.151	(0.180)	-0.829	(0.061)	-0.435	(0.048)	-1.107	(0.116)	-0.743	(0.044)
Displaced at *t*-5	-0.494	(0.060)	-0.680	(0.157)	-0.700	(0.060)	-0.281	(0.048)	-0.636	(0.116)	-0.613	(0.044)
Displaced at *t*-6	-0.291	(0.052)	-0.362	(0.136)	-0.418	(0.050)	-0.078	(0.048)	-0.317	(0.116)	-0.333	(0.044)
Displaced at *t*-7	-0.162	(0.044)	0.068	(0.093)	-0.180	(0.040)	0.050	(0.048)	0.113	(0.116)	-0.095	(0.044)
No. of observations	1038972						1038972					
R-squared	0.0477						0.0217					

The dependent variable is months of employment. Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared, regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 7B The effect of displacement on *earnings* by displacement type

	OLS						FE					
	Exit layoffs		Early leavers		Down-sizing separators		Exit layoffs		Early leavers		Down-sizing separators	
Displaced at *t*+3	-0.037	(0.006)	0.001	(0.015)	-0.031	(0.006)						
Displaced at *t*+2	-0.031	(0.006)	0.007	(0.013)	-0.038	(0.005)	0.005	(0.006)	0.005	(0.013)	-0.007	(0.005)
Displaced at *t*+1	-0.028	(0.005)	-0.019	(0.011)	-0.031	(0.006)	0.008	(0.006)	-0.021	(0.013)	0.000	(0.005)
Displaced at *t*	-0.036	(0.005	-0.030	(0.013)	-0.033	(0.006)	0.000	(0.006)	-0.032	(0.013)	-0.003	(0.005)
Displaced at *t*-1	-0.044	(0.006)	-0.058	(0.017)	-0.061	(0.006)	-0.008	(0.006)	-0.060	(0.013)	-0.030	(0.005)
Displaced at *t*-2	-0.061	(0.006)	-0.103	(0.020)	-0.073	(0.007)	-0.026	(0.006)	-0.105	(0.013)	-0.043	(0.005)
Displaced at *t*-3	-0.055	(0.006)	-0.077	(0.020)	-0.065	(0.007)	-0.020	(0.006)	-0.079	(0.013)	-0.035	(0.005)
Displaced at *t*-4	-0.054	(0.007)	-0.070	(0.022)	-0.069	(0.008)	-0.019	(0.006)	-0.072	(0.013)	-0.038	(0.005)
Displaced at *t*-5	-0.043	(0.007)	-0.038	(0.019)	-0.037	(0.007)	-0.007	(0.006)	-0.040	(0.013)	-0.007	(0.005)
Displaced at *t*-6	-0.044	(0.008)	-0.029	(0.020)	-0.036	(0.007)	-0.009	(0.006)	-0.031	(0.013)	-0.005	(0.005)
Displaced at *t*-7	-0.028	(0.008)	0.009	(0.015)	-0.022	(0.008)	0.008	(0.006)	0.006	(0.013)	0.008	(0.005)
No. of observations	1038972						1038972					
R-squared	0.2640						0.0743					

The dependent variable is ln(annual earnings). Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared, regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 8A The effect of displacement on *employment* by pre-displacement age

	OLS				FE			
	Age < 45		Age ≥ 45		Age < 45		Age ≥ 45	
Displaced at *t+3*	-0.145	(0.031)	-0.094	(0.030)				
Displaced at *t*+2	-0.283	(0.034)	-0.185	(0.037)	-0.140	(0.037)	-0.095	(0.058)
Displaced at *t+1*	-0.319	(0.031)	-0.163	(0.028)	-0.173	(0.037)	-0.071	(0.058)
Displaced at *t*	-0.332	(0.018)	-0.383	(0.025)	-0.182	(0.037)	-0.290	(0.058)
Displaced at *t-1*	-2.061	(0.064)	-1.917	(0.098)	-1.908	(0.037)	-1.823	(0.058)
Displaced at *t-2*	-1.486	(0.059)	-1.289	(0.089)	-1.333	(0.037)	-1.195	(0.058)
Displaced at *t-3*	-1.181	(0.056)	-0.994	(0.084)	-1.026	(0.037)	-0.899	(0.059)
Displaced at *t-4*	-0.795	(0.051)	-0.725	(0.077)	-0.639	(0.037)	-0.632	(0.059)
Displaced at *t-5*	-0.642	(0.049)	-0.536	(0.073)	-0.486	(0.037)	-0.444	(0.059)
Displaced at *t-6*	-0.322	(0.041)	-0.461	(0.068)	-0.166	(0.037)	-0.371	(0.059)
Displaced at *t-7*	-0.113	(0.032)	-0.265	(0.058)	0.043	(0.037)	-0.178	(0.059)
No. of observations	1038972				1038972			
R-squared	0.2641				0.0743	(within)		

The dependent variable is months of employment. Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 8B The effect of displacement on *earnings* by pre-displacement age

	OLS				FE			
	Age < 45		Age ≥ 45		Age < 45		Age ≥ 45	
Displaced at *t+3*	-0.028	(0.005)	-0.038	(0.007)				
Displaced at *t*+2	-0.026	(0.004)	-0.047	(0.007)	0.002	(0.004)	-0.009	(0.007)
Displaced at *t+1*	-0.023	(0.004)	-0.044	(0.007)	0.005	(0.004)	-0.006	(0.007)
Displaced at *t*	-0.026	(0.004)	-0.054	(0.007)	0.001	(0.004)	-0.016	(0.007)
Displaced at *t-1*	-0.047	(0.005)	-0.069	(0.008)	-0.020	(0.004)	-0.031	(0.007)
Displaced at *t-2*	-0.066	(0.006)	-0.081	(0.008)	-0.038	(0.004)	-0.044	(0.007)
Displaced at *t-3*	-0.056	(0.006)	-0.077	(0.009)	-0.029	(0.004)	-0.039	(0.007)
Displaced at *t-4*	-0.059	(0.007)	-0.071	(0.009)	-0.032	(0.004)	-0.033	(0.007)
Displaced at *t-5*	-0.031	(0.006)	-0.061	(0.010)	-0.004	(0.004)	-0.023	(0.007)
Displaced at *t-6*	-0.029	(0.006)	-0.064	(0.010)	-0.002	(0.004)	-0.027	(0.007)
Displaced at *t-7*	-0.005	(0.006)	-0.067	(0.011)	0.022	(0.004)	-0.029	(0.007)
No. of observations	1038972				1038972			
R-squared	0.2641				0.0743	(within)		

The dependent variable is ln(annual earnings). Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 9A The effect of displacement on *employment* by pre-displacement tenure

	OLS				FE			
	Tenure < 3		Tenure ≥ 3		Tenure < 3		Tenure ≥ 3	
Displaced at *t+3*	0.001	(0.055)	-0.093	(0.019)				
Displaced at *t*+2	-0.452	(0.064)	-0.014	(0.014)	-0.457	(0.050)	0.077	(0.040)
Displaced at *t+1*	-0.269	(0.057)	-0.160	(0.015)	-0.272	(0.050)	-0.065	(0.040)
Displaced at *t*	-0.028	(0.029)	-0.424	(0.016)	-0.031	(0.050)	-0.325	(0.040)
Displaced at *t-1*	-1.896	(0.091)	-1.979	(0.066)	-1.895	(0.050)	-1.878	(0.040)
Displaced at *t-2*	-1.472	(0.087)	-1.286	(0.060)	-1.469	(0.050)	-1.186	(0.040)
Displaced at *t-3*	-1.335	(0.087)	-0.881	(0.053)	-1.333	(0.050)	-0.779	(0.040)
Displaced at *t-4*	-0.707	(0.078)	-0.698	(0.049)	-0.704	(0.050)	-0.597	(0.040)
Displaced at *t-5*	-0.445	(0.074)	-0.596	(0.048)	-0.442	(0.050)	-0.494	(0.040)
Displaced at *t-6*	-0.127	(0.065)	-0.386	(0.040)	-0.126	(0.050)	-0.284	(0.040)
Displaced at *t-7*	0.228	(0.052)	-0.273	(0.033)	0.228	(0.050)	-0.173	(0.040)
No. of observations	1038972				1038972			
R-squared	0.0536				0.0209	(within)		

The dependent variable is months of employment. Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 9B The effect of displacement on *earnings* by pre-displacement tenure

	OLS				FE			
	Tenure < 3		Tenure ≥ 3		Tenure < 3		Tenure ≥ 3	
Displaced at *t+3*	-0.012	(0.007)	-0.035	(0.005)				
Displaced at *t*+2	-0.023	(0.007)	-0.030	(0.004)	-0.011	(0.006)	0.005	(0.005)
Displaced at *t+1*	-0.016	(0.007)	-0.030	(0.005)	-0.003	(0.006)	0.006	(0.005)
Displaced at *t*	-0.011	(0.006)	-0.042	(0.005)	0.002	(0.006)	-0.007	(0.005)
Displaced at *t-1*	-0.035	(0.007)	-0.057	(0.006)	-0.023	(0.006)	-0.023	(0.005)
Displaced at *t-2*	-0.063	(0.008)	-0.068	(0.006)	-0.051	(0.006)	-0.033	(0.005)
Displaced at *t-3*	-0.056	(0.009)	-0.059	(0.006)	-0.044	(0.006)	-0.024	(0.005)
Displaced at *t-4*	-0.047	(0.009)	-0.065	(0.007)	-0.036	(0.006)	-0.030	(0.005)
Displaced at *t-5*	-0.033	(0.008)	-0.037	(0.006)	-0.021	(0.006)	-0.003	(0.005)
Displaced at *t-6*	-0.026	(0.009)	-0.040	(0.006)	-0.014	(0.006)	-0.005	(0.005)
Displaced at *t-7*	-0.008	(0.009)	-0.024	(0.007)	0.004	(0.006)	0.010	(0.005)
No. of observations	1038972				1038972			
R-squared	0.2647				0.036	(within)		

The dependent variable is ln(annual earnings). Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 10A The effect of displacement on *employment* by education

	OLS				FE			
	Education ≤ 10		Education > 10		Education ≤ 10		Education > 10	
Displaced at *t+3*	-0.090	(0.036)	-0.162	(0.032)				
Displaced at *t*+2	-0.277	(0.041)	-0.233	(0.034)	-0.191	(0.046)	-0.073	(0.043)
Displaced at *t+1*	-0.254	(0.035)	-0.290	(0.032)	-0.166	(0.046)	-0.125	(0.043)
Displaced at *t*	-0.411	(0.024)	-0.286	(0.018)	-0.322	(0.046)	-0.118	(0.043)
Displaced at *t-1*	-2.496	(0.084)	-1.605	(0.068)	-2.404	(0.046)	-1.434	(0.043)
Displaced at *t-2*	-1.987	(0.080)	-0.945	(0.060)	-1.893	(0.046)	-0.775	(0.043)
Displaced at *t-3*	-1.465	(0.074)	-0.832	(0.058)	-1.372	(0.046)	-0.660	(0.043)
Displaced at *t-4*	-1.004	(0.067)	-0.572	(0.054)	-0.911	(0.046)	-0.400	(0.043)
Displaced at *t-5*	-0.828	(0.065)	-0.420	(0.051)	-0.735	(0.046)	-0.247	(0.043)
Displaced at *t-6*	-0.534	(0.057)	-0.206	(0.043)	-0.442	(0.046)	-0.034	(0.043)
Displaced at *t-7*	-0.255	(0.048)	-0.065	(0.033)	-0.164	(0.046)	0.107	(0.043)
No. of observations	1038972				1038972			
R-squared	0.0477				0.0212	(within)		

The dependent variable is months of employment. Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 10B The effect of displacement on *earnings* by education

	OLS				FE			
	Education ≤ 10		Education > 10		Education ≤ 10		Education > 10	
Displaced at *t+3*	-0.007	(0.005)	-0.052	(0.006)				
Displaced at *t*+2	-0.022	(0.005)	-0.041	(0.005)	-0.015	(0.005)	0.011	(0.005)
Displaced at *t+1*	-0.022	(0.006)	-0.035	(0.005)	-0.015	(0.005)	0.017	(0.005)
Displaced at *t*	-0.033	(0.005)	-0.036	(0.005)	-0.026	(0.005)	0.015	(0.005)
Displaced at *t-1*	-0.067	(0.006)	-0.042	(0.006)	-0.060	(0.005)	0.009	(0.005)
Displaced at *t-2*	-0.093	(0.007)	-0.051	(0.006)	-0.086	(0.005)	0.000	(0.005)
Displaced at *t-3*	-0.081	(0.007)	-0.046	(0.006)	-0.074	(0.005)	0.005	(0.005)
Displaced at *t-4*	-0.081	(0.008)	-0.047	(0.007)	-0.074	(0.005)	0.003	(0.005)
Displaced at *t-5*	-0.061	(0.007)	-0.021	(0.006)	-0.054	(0.005)	0.029	(0.005)
Displaced at *t-6*	-0.064	(0.008)	-0.018	(0.007)	-0.056	(0.005)	0.033	(0.005)
Displaced at *t-7*	-0.052	(0.008)	0.003	(0.007)	-0.045	(0.005)	0.053	(0.005)
No. of observations	1038972				1038972			
R-squared	0.2648				0.0746	(within)		

The dependent variable is months of ln(annual earnings). Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 11A The effect of displacement on *employment* by pre-displacement plant size

	OLS				FE			
	Pl.size < 100		Pl.size ≥ 100		Pl.size < 100		Pl.size ≥ 100	
Displaced at *t+3*	-0.153	(0.044)	-0.079	(0.026)				
Displaced at *t*+2	-0.332	(0.048)	-0.163	(0.029)	-0.177	(0.047)	-0.090	(0.042)
Displaced at *t+1*	-0.287	(0.043)	-0.232	(0.027)	-0.134	(0.047)	-0.152	(0.042)
Displaced at *t*	-0.373	(0.026)	-0.291	(0.017)	-0.218	(0.047)	-0.207	(0.042)
Displaced at *t-1*	-3.173	(0.094)	-1.097	(0.058)	-3.018	(0.047)	-1.008	(0.042)
Displaced at *t-2*	-2.262	(0.087)	-0.755	(0.055)	-2.107	(0.047)	-0.665	(0.042)
Displaced at *t-3*	-1.547	(0.080)	-0.771	(0.055)	-1.393	(0.047)	-0.678	(0.042)
Displaced at *t-4*	-1.044	(0.072)	-0.533	(0.050)	-0.890	(0.047)	-0.441	(0.042)
Displaced at *t-5*	-0.776	(0.069)	-0.450	(0.049)	-0.622	(0.047)	-0.358	(0.042)
Displaced at *t-6*	-0.406	(0.059)	-0.291	(0.042)	-0.251	(0.047)	-0.200	(0.042)
Displaced at *t-7*	-0.108	(0.048)	-0.157	(0.034)	0.047	(0.047)	-0.069	(0.042)
No. of observations	1038972				1038972			
R-squared	0.0495				0.0230	(within)		

The dependent variable is months of employment. Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 11B   The effect of displacement on *earnings* by pre-displacement plant size

	OLS				FE			
	Pl. size < 100		Pl.size ≥ 100		Pl.size < 100		Pl.size ≥ 100	
Displaced at *t+3*	-0.007	(0.007)	-0.044	(0.005)				
Displaced at *t*+2	-0.017	(0.006)	-0.038	(0.005)	-0.010	(0.005)	0.007	(0.005)
Displaced at *t+1*	-0.012	(0.007)	-0.036	(0.004)	-0.005	(0.005)	0.008	(0.005)
Displaced at *t*	-0.040	(0.006)	-0.025	(0.004)	-0.033	(0.005)	0.019	(0.005)
Displaced at *t-1*	-0.059	(0.008)	-0.043	(0.005)	-0.053	(0.005)	0.000	(0.005)
Displaced at *t-2*	-0.084	(0.008)	-0.054	(0.005)	-0.078	(0.005)	-0.010	(0.005)
Displaced at *t-3*	-0.069	(0.008)	-0.051	(0.006)	-0.062	(0.005)	-0.008	(0.005)
Displaced at *t-4*	-0.072	(0.009)	-0.050	(0.006)	-0.066	(0.005)	-0.007	(0.005)
Displaced at *t-5*	-0.050	(0.008)	-0.026	(0.006)	-0.044	(0.005)	0.017	(0.005)
Displaced at *t-6*	-0.046	(0.008)	-0.028	(0.006)	-0.040	(0.005)	0.016	(0.005)
Displaced at *t-7*	-0.027	(0.008)	-0.014	(0.007)	-0.020	(0.005)	0.030	(0.005)
No. of observations	1038972				1038972			
R-squared	0.2649				0.0744	(within)		

The dependent variable is months of ln(annual earnings). Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 12A The effect of displacement on *employment* by pre-displacement labour market size

	OLS				FE			
	Lab.m. size < 50 000		Lab.m. size ≥ 50 000		Lab.m. size < 50 000		Lab.m. size ≥ 50 000	
Displaced at *t+3*	-0.101	(0.039)	-0.155	(0.031)				
Displaced at *t*+2	-0.229	(0.041)	-0.279	(0.035)	-0.136	(0.047)	-0.121	(0.042)
Displaced at *t+1*	-0.259	(0.035)	-0.289	(0.033)	-0.169	(0.047)	-0.125	(0.042)
Displaced at *t*	-0.335	(0.023)	-0.355	(0.019)	-0.242	(0.047)	-0.188	(0.042)
Displaced at *t-1*	-2.252	(0.083)	-1.835	(0.070)	-2.159	(0.047)	-1.664	(0.042)
Displaced at *t-2*	-1.628	(0.077)	-1.273	(0.064)	-1.533	(0.047)	-1.102	(0.042)
Displaced at *t-3*	-1.172	(0.072)	-1.092	(0.062)	-1.078	(0.047)	-0.920	(0.042)
Displaced at *t-4*	-0.782	(0.065)	-0.768	(0.057)	-0.686	(0.047)	-0.598	(0.042)
Displaced at *t-5*	-0.616	(0.062)	-0.608	(0.055)	-0.519	(0.047)	-0.437	(0.042)
Displaced at *t-6*	-0.310	(0.052)	-0.400	(0.048)	-0.215	(0.047)	-0.229	(0.042)
Displaced at *t-7*	-0.144	(0.043)	-0.164	(0.038)	-0.049	(0.047)	0.005	(0.042)
No. of observations	1038972				1038972			
R-squared	0.0466				0.0206	(within)		

The dependent variable is months of employment. Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 12B The effect of displacement on *earnings* by pre-displacement labour market size

	OLS				FE			
	Lab.m. size < 50 000		Lab.m. size ≥ 50 000		Lab.m. size < 50 000		Lab.m. size ≥ 50 000	
Displaced at *t+3*	-0.010	(0.005)	-0.048	(0.006)				
Displaced at *t*+2	-0.014	(0.005)	-0.047	(0.006)	-0.003	(0.005)	0.001	(0.005)
Displaced at *t+1*	-0.012	(0.005)	-0.043	(0.005)	0.000	(0.005)	0.004	(0.005)
Displaced at *t*	-0.020	(0.005)	-0.046	(0.005)	-0.009	(0.005)	0.001	(0.005)
Displaced at *t-1*	-0.054	(0.006)	-0.052	(0.006)	-0.042	(0.005)	-0.007	(0.005)
Displaced at *t-2*	-0.064	(0.007)	-0.074	(0.007)	-0.053	(0.005)	-0.029	(0.005)
Displaced at *t-3*	-0.052	(0.007)	-0.069	(0.007)	-0.041	(0.005)	-0.025	(0.005)
Displaced at *t-4*	-0.057	(0.007)	-0.066	(0.008)	-0.047	(0.005)	-0.021	(0.005)
Displaced at *t-5*	-0.032	(0.007)	-0.045	(0.007)	-0.021	(0.005)	-0.001	(0.005)
Displaced at *t-6*	-0.035	(0.008)	-0.041	(0.007)	-0.024	(0.005)	0.004	(0.005)
Displaced at *t-7*	-0.017	(0.007)	-0.027	(0.008)	-0.005	(0.005)	0.018	(0.005)
No. of observations	1038972				1038972			
R-squared	0.2643				0.0743	(within)		

The dependent variable is ln(annual earnings). Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. Robust standard errors are in parenthesis.

Table 13A The effect of displacement on *employment* by growth of the pre-displacement industry

	OLS				FE			
	Sunset		Other		Sunset		Other	
Displaced at *t+3*	0.033	(0.042)	-0.208	(0.029)				
Displaced at *t*+2	-0.063	(0.045)	-0.347	(0.033)	-0.097	(0.055)	-0.142	(0.038)
Displaced at *t+1*	-0.156	(0.041)	-0.332	(0.030)	-0.190	(0.055)	-0.122	(0.038)
Displaced at *t*	-0.337	(0.028)	-0.350	(0.017)	-0.369	(0.055)	-0.138	(0.038)
Displaced at *t-1*	-2.413	(0.101)	-1.833	(0.063)	-2.444	(0.055)	-1.618	(0.038)
Displaced at *t-2*	-2.003	(0.096)	-1.159	(0.057)	-2.034	(0.055)	-0.943	(0.038)
Displaced at *t-3*	-1.540	(0.091)	-0.932	(0.054)	-1.572	(0.055)	-0.715	(0.038)
Displaced at *t-4*	-1.062	(0.083)	-0.638	(0.049)	-1.093	(0.055)	-0.421	(0.038)
Displaced at *t-5*	-0.845	(0.079)	-0.500	(0.047)	-0.875	(0.055)	-0.283	(0.038)
Displaced at *t-6*	-0.473	(0.069)	-0.306	(0.040)	-0.503	(0.055)	-0.090	(0.038)
Displaced at *t-7*	-0.239	(0.058)	-0.114	(0.032)	-0.269	(0.055)	0.100	(0.038)
No. of observations	1038972				1038972			
R-squared	0.0472				0.0211	(within)		

The dependent variable is months of employment. Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. The sunset industries are 5 digit-industries with 15 percent (or more) decline in relative employment between 1980 and 1990. Robust standard errors are in parenthesis.

Table 13B The effect of displacement on *earnings* by growth of the pre-displacement industry

	OLS				FE			
	Sunset		Other		Sunset		Other	
Displaced at *t+3*	0.018	(0.006)	-0.057	(0.005)				
Displaced at *t*+2	0.002	(0.006)	-0.051	(0.005)	-0.016	(0.006)	0.006	(0.004)
Displaced at *t+1*	0.000	(0.006)	-0.045	(0.005)	-0.019	(0.006)	0.012	(0.004)
Displaced at *t*	-0.017	(0.006)	-0.045	(0.005)	-0.035	(0.006)	0.011	(0.004)
Displaced at *t-1*	-0.058	(0.007)	-0.054	(0.005)	-0.076	(0.006)	0.002	(0.004)
Displaced at *t-2*	-0.085	(0.009)	-0.066	(0.006)	-0.103	(0.006)	-0.010	(0.004)
Displaced at *t-3*	-0.071	(0.009)	-0.060	(0.006)	-0.089	(0.006)	-0.004	(0.004)
Displaced at *t-4*	-0.081	(0.010)	-0.057	(0.006)	-0.099	(0.006)	-0.001	(0.004)
Displaced at *t-5*	-0.055	(0.009)	-0.035	(0.006)	-0.073	(0.006)	0.021	(0.004)
Displaced at *t-6*	-0.049	(0.009)	-0.037	(0.006)	-0.068	(0.006)	0.019	(0.004)
Displaced at *t-7*	-0.034	(0.009)	-0.020	(0.007)	-0.053	(0.006)	0.036	(0.004)
No. of observations	1038972				1038972			
R-squared	0.2676				0.0746	(within)		

The dependent variable is ln(annual earnings). Displacements happened between May 1991 and May 1992. *t* is the year of the observation. The sample covers the years 1988 to 1998, and consists of 25-55 year old male workers, full time employed in manufacturing in 1991, who were in the labour force and not displaced from their jobs in the previous three years, and who were in the labour force in the last observed post displacement year, 1998. The following control variables are included, but not reported: Age, age squared and regional rate of unemployment and time dummies. The specification without fixed effects also includes years of schooling, tenure when displaced, marital status when displaced, plant size when displaced, size of the regional labour market when displaced, industry and region dummies. The sunset industries are 5 digit-industries with 15 percent (or more) decline in relative employment between 1980 and 1990. Robust standard errors are in parenthesis.

V Worker Turnover in Dying Plants and Re-employment Wages

Abstract

This paper examines worker turnover in dying plants. The hypothesis is that the knowledge of future economic distress will influence both firm's hiring and firing decisions, as well as the workers' quitting decisions. As a result, workers' post-displacement earning losses are likely to differ between workers who leave the dying firm in different stages. The results using matched employer-employee panel data from Norway show that there are significant changes in workforce skill mix before the plant closure. Workers who decide to leave the dying plants early suffer no wage losses in their re-employment jobs, while the ones who stay until the end suffer significant earning losses. On the other hand, workers who are laid off in the period before the plant's death suffer even more severe earnings reductions.

1 Introduction

The relationship between job tenure and wages has been subject of considerable interest in empirical labour economics for decades[1]. A well-known challenge in these studies is the possible endogeneity of worker mobility, and thus of the job tenure. As high ability workers are likely to have better job matches, they are also less likely to leave the firm or to be fired, and hence end up with more tenure. A popular strategy to overcome this difficulty has been to focus on workers who loose their jobs due to plant closure[2]. The argument in these studies is that plant closure is an result of an exogenous shock, which results in a separation of all plant's workers. Thus, workers who were displaced by plant closure are random sample of workforce and not selected on the basis of their past choice.

This argument relies on assumption that plant closure happens instantly and cannot be predicted. It is, however, more realistic to assume that both workers and firm have time to react before the actual closing down occurs. Previous empirical findings support this assumption: a plant closure is often preceded by a period of significant downsizing[3]. Given the knowledge of future economic distress, both firm and workers might engage in strategic behavior to minimize the costs associated with this event. When troubled firm is forced to layoff a share of its workers, it gets rid of the least productive ones. In addition, the workers with relatively better external market opportunities are more likely to quit voluntarily from these plants. The remaining sample of workers is thus a selected sample of the workers who are affected by the shock that lead to plant closing down.

This paper examines empirically whether there is a selective turnover of workers in a plant before its closure, and whether this influences the post-

[1]See e.g. Altonji and Shakotko (1987) and Topel (1991).

[2]See e.g. Gibbons and Katz (1992) and Dustman and Meghir (2005).

[3]It is also well-established finding that dying plants have lower levels and growth rates of productivy several years before the death occurs. This is the "shadow of death effect" (see e.g. Griliches and Regev, 1995).

displacement earning losses. The hypothesis is that the knowledge of future economic distress will influence both firm's hiring and firing decisions, as well as the workers' quitting decisions. The firm chooses to retain its most productive workers, while workers with relatively better external market opportunities and lower proportion of firm-specific human capital are more likely to quit. As a result of this selection process, workers' re-employment wages and post-displacement earning losses are likely to differ between workers who leave the dying firm in different stages. Workers who decided to leave earlier are assumed to have smaller post-displacement earning losses, than the ones who decide to stay. On the other hand, workers that are laid off before the closure occurs are expected to suffer more severe reductions in their post-displacement earnings than the ones who remain with their employer until the end.

The empirical analysis can be divided into two parts. First, we examine whether there are significant changes in the workforce skill distribution before the plant closure and whether workers who leave the dying plants in different stages differ significantly by their observable characteristics. Second, we examine whether there are significant differences in the post-displacement earning losses of workers who leave the dying plant in different stages. This allows us to study whether this selection process in dying plants affects the magnitude of post-displacement earnings losses.

Our analysis is based on matched employee-employer panel data from Norway for 1988-2000. The results are consistent with the theoretical predictions. There are significant changes in the workforce skill mix before the plant closure. Workers who decide to leave the dying plants early suffer no wage losses in their re-employment jobs, while the ones who stay until the end suffer significant earning losses. On the other hand, workers who are laid off in the period before the plant's death suffer even more severe earnings reductions.

The paper is organized as follows. Section 2 briefly discusses the theoretical framework for our analysis and summaries the main predictions. Section 3 describes the data. Section 4 presents the statistical methodology used in this paper. Section 5 reports the results, and section 6 concludes.

2 Theoretical Discussion and Previous Evidence

2.1 Theoretical Discussion

The basic job search model serves as an adequate framework for discussing the effect of future plant closure on worker's behavior (see e.g. Mortensen, 1986)[4]. In such model, workers maximize the expected present value of their future income stream. While on-the-job they receive wage offers, ω, from prospective employers. The location of the wage offer distribution depends on worker's characteristics (human capital)[5]. The worker accepts ω if and only if it exceed the reservation wage ω_r. A knowledge of future closure lowers the value of employment in a given firm, since the likelihood of ending into unemployment increases[6]. This lowers worker's reservation wages, increases worker's search intensity, and as a consequence increases the number of job offers he receives. Workers with better outside opportunities, e.g. higher share of general human capital, will engage in on-the-job-search more intensively than the ones with lower share of general human capital. As

[4] The search framework is typically used in studies which examine the effect of advance notice of job displacement on post-displacement outcomes. See e.g. Addison and Portugal (1987), Ruhm (1994) and Friesen (1997).

[5] It thus differs among individuals and may also shift during workers career as general human capital accumulates. see e.g. Topel et Ward, 1992

[6] We assume that all the plant's workers receive simultaneously the knowledge of future plant closure. It might be, however, that different type of workers are more likely to be informed. E.g. if employers are concerned that best workers leave more easily, then they might try to withold this information from them. Thus, those workers who are most likely to find and take new jobs before the scheduled layoff may be least likely to be notified (see Fallick, 1994). On the otherhand, as stated in Ruhm (1997), when entire plant is being closed, it will be more difficult to to selectively inform workers of impending displacement.

a consequence, workers with high share of general human capital are more likely to receive and accept wage offers. Thus, the knowledge of future shock increases disproportionately the quit rates of these workers.

Firm is assumed to maximizes its expected net present value of profits. A negative shock leads to reductions in the level of demand for firm's product, and consequently reductions in demand for labour. Firm's decision whom to fire depends on adjustment costs and on worker's productivity. Workers with low firing costs and low expected productivity growth are more likely to be laid off. The firm is indifferent between two ways it can get rid of the worker: it can lay off the worker, or it can induce worker to quit by offering less than a market wage.

Following the literature on asymmetric information on labour market (Gibbons and Katz, 1991, Laing, 1993), we assume that worker's current employer is better informed about his or her ability than alternative employers. This is because part of worker's ability is privately learned by the firm (and workers) after a period of employment. The prospective employers infer worker quality from the publicly observable actions taken by the firm[7]. The market infers that laid-off workers are of low ability and so offers them low wages in their next jobs. We assume, as in Gibbons and Katz, (1991), that workers displaced by plant closing suffer from no such adverse inference and so receive higher re-employment wages from labour market.

These theoretical considerations provides some prediction that are relevant to this analysis. First, in the period before the plant is shut down there are significant changes in the workforce skill distribution: Worker's with highest share of general human capital, i.e. observable skills such as education and general experience, are more likely to quit voluntarily, and employer is more likely to fire the least productive ones, i.e. the ones with low share

[7] Farber and Gibbons (1996) call this "private learning", i.e. a case where only worker and the current employer observe performance outcomes, but other market participants draw appropriate inference from the observed actions of the worker and the current employer.

of both observable and non-observable skills. The remaining workers should have higher share of firm-specific human capital, i.e. more tenure and unobservable skills. Second, workers' re-employment wages and pre-displacement earning losses depend on the mode of separation: Workers who quit voluntarily should suffer less severe reduction (or bigger increase) in their earnings, than the ones who decide to stay until the plant closure. On the other hand, workers who are laid-off in the period before the closure should suffer bigger reduction in their wages than the ones who are displaced at the moment plant was shut down.

2.2 Previous evidence

Very few studies have examined empirically whether there is indeed a selection process within plants before their death, and whether this has an implications to post-displacement earning losses. The main reason for this is data limitations. In order to fully explore the question both data on firms and workers before and after the separation is needed. To our knowledge only three previous papers have addressed this question directly. Lengermann and Vilhuber (2002) examine the changes in the composition of job and worker flows prior to "mass-layoff event" (plant closure or significant downsizing) using on quarterly earning records of workers in the state of Maryland. The quantile regression analysis reveal that there are significant changes in the distribution of worker quality[8] in separation flows prior to plant shut down. Compared to job flows from non-distressed firms the distribution of skill in worker flows from dying and downsizing firms has much higher variance, indicating that both the best and worst workers leave the firm before the actual closure or mass layoff event. Bowlus and Vilhuber (2002) examine whether the workers who leave before the actual mass-layoff event, will on average have higher accepted wages than workers who are dis-

[8] The measure for worker quality or skill is derived from person fixed effects estimated using the wage regression techniques pioneered by Abowd, Kramarz, and Margolis (1999).

placed during the mass-layoff event (plant closing down). They use data from US universal wage records to test this hypothesis. They findings suggest that workers leaving a firm that will close down or downsize significantly have higher re-employment wages than workers who stay with this firm until the mass layoff event. Hamermesh and Pfann (2001) construct a dynamic model of two-sided learning between firm and workers in the presence of negative shocks. They test the implications of the model using data from one big Dutch company, Fokker Aircraft. The results imply that the firm learn which employees are likely to quit, and alters its layoff decisions accordingly. The data reveal that there is important selection process going on in the firm before the bankruptcy, and that workers staying with the firm until its closure are disproportionately male, married, technically educated, have longer tenure, and more internal training courses.

3 Data

3.1 Description of the data source

The base data set for this study come from administrative registers and prepared for research by Statistics Norway. It covers all 16-74 year old Norwegians in the years 1986-2000. The data provides information about ongoing employment relations such as starting and stopping date of employment relation, taxable income, educational attainment, labour market status, and a set of demographic variables. The main demographic variables used in this analysis are annual income (both from main employer and from other sources), tenure, which is calculated in years on the basis of starting and stopping date information, worker's age, years of schooling and marital status.

Each of the workers and their employers, and their municipalities have a unique identification code that can be used to merge in additional information from other sources, such as information on worker's health, family background, local labor market characteristic. The unique identification code allows us to follow workers where ever they go in Norwegian economy. The unique plant code allows us to identify each worker's plants and examine e.g. whether they go trough a significant downsizing or close down. We use plant codes to define worker's separation status. Worker is a *separator* at time t if at time t+1 he no longer has the same plant identification number.

3.2 Sample Construction

The sample of workers analyzed in this article is constructed as follows. From the overall data base, we first draw a 10 % random sample of plants observed in (base) year 1995, and which had been in the data set at least 3 years before (i.e. in years 1992-1994). Thus each plant is in the sample at least 4 years. Plants are divided into exiting plants and non-exiting plants. Plant is an exiting plant in year t if it is present in year t but absent in $t+1$, $t+2$, $t+3$ and $t+4$. The whole base year sample consists of 7621 plants with 120 453 workers in 1995 (see table 1). The number of exiting plants in 1995 is 415 and the number of workers in these plants is 4226.

Next we form two different data sets using this base year sample. In order to examine the pre-exit turnover we match these *plants* to the information on *their* workers in years 1992-1995. That is, we follow the workers who were employed in these *plants* in four different pre-exit years. Consequently we have a panel of workers who were working in these plants in any of the years 1992-1995. We have thus information on both the workers who were continuously employed in these plants until the base year 1995, and the workers who left these plants before the base year.

In addition, we form a balanced panel matching the *workers* who were employed in these plants in the base year (1995) to *their* information on both pre-and post-exit years to examine the evaluation of pre- and post-displacement wages. This gives us a balanced panel of workers from 1992-

1998 with 795 094 observations[9].

Workers in exiting plants are divided into four different categories according to their separation status. First we define two main categories. We label a worker as a *stayer* (or an *exit-layoff)* if he was working in an exiting plant at the moment the plant was last observed (t). Thus, *exit-layoffs* separated from the exiting plant in the period when the plant closed down, i.e. between t and $t+1$. Workers who leave the dying plant before are labeled as *leavers (*or *early-leavers)*. Worker is an *early-leaver* if he separated between $t-1$ and t from a plant that exited between t and $t+1$.

Both of these two main categories are further divided into two subcategories. Worker is a *job-to-job mover* at t if he separated from a plant between t and $t+1$, is attached to a new plant in period $t+1$, and did not experience any unemployment spells in either t or $t+1$. These workers are considered as the voluntary separators. Consequently, separators who do not fulfill these criteria are labeled as *not-job-to-job movers.* Thus, all together we have five different worker categories: 1. stayers in exiting plants who moved directly to new jobs: *job-to-job exit-layoffs*, 2. stayers in exiting plants who may not have moved directly to new job: *not-job-to-job exit-layoffs*, 3. workers who are expected to leave the dying plant voluntarily in the period before the closure: *job-to-job early-leavers*, 4. workers who were expected to be laid off in the period before the plant closed down: *not-to-job early-leavers*, and 5. *other workers*, which include both stayers and separators from continuous plants.

4 Empirical framework

The object of this study is to examine empirically whether there is evidence of selective turnover in the plants before the closure occurs. The empirical

[9] This is after dropping the observations that do not have information on all the relevant characteristics.

framework consists of two different steps. First we examine whether there are significant changes in the distribution of worker quality before the plant closure and whether workers who leave a dying plant in different stages differ by their observable characteristics. Second, we analyze whether this selection process implies that there are differences in the re-employment wages of the workers who leave the firm in different periods.

4.1 Examining the pre-closure turnover

The aim in this section is to examine whether there is significant turnover in plants before the closure and whether this turnover changes the skill mix of workers within the plants. We use different measures for worker quality (or skill), such as, years of education, age, tenure and logarithm of annual earnings. We provide descriptive information to examine whether the skill distribution of workers change in plants when the closure approaches. It might be that the future closure has an effect on the shape of the skill distribution, but not necessary on its location. Thus, in addition on providing information on how the mean of these variables changes we also look how does the entire distribution change within exiting plants.

The fact that skill mix within dying plants is changing as compared to continuing plants can be result of different phenomena. Troubled plants are likely to reduce the number of their employees by firing the workers with lowest productivity/pay relation and lowest firing costs. It might also be that troubled firms stop recruiting, and that the average age and tenure are increasing simply because existing workforce is getting older. Dying plants might also continue recruiting and try to prevent possible closure replacing their existing workers with new employees, and generally improving the "quality" of their workforce. In order to distinguish between these possibilities we examine the composition of worker flows from the plants in different pre-closure years.

Finally, we examine in more detail whether workers with certain characteristics are more likely to leave the dying plants before the closure by estimating a standard probit model. The probability of leaving a dying plant in a period before the closure occurs can be written as a following standard probit model

$$P(y_{i,t} = 1|\mathbf{x}_{i,t}) = \Phi\left(\mathbf{x}_{i,t}\beta\right) \tag{1}$$

where $y_{i,t}$ is an indicator variable describing whether worker i separated between time $t-1$ and t from a plant that died between t and $t+1$, and $\mathbf{x}_{i,t}$ is a vector of factors that affect this probability. These factors include both worker, plant, industry and local labour market characteristics, as well as common time specific factors.

4.2 Estimating post-displacement earning losses

In the second stage we estimate the effect of job displacement on workers reemployment wages. The estimated equation follows the specifications used in previous studies (e.g. Jacobson et al. 1993, Stevens, 1997) with some important extensions:

$$\log(W)_{i,t} = \mathbf{X}_{i,t}\beta + \sum_{j=-m}^{k} EXIT_{i,t-j}\gamma_j + \sum_{j=-m}^{k} EARLY_{i,t-j}\gamma_j + \mu_{i,t} \tag{2}$$

where $\log(W)_{i,t}$ is the logarithm of annual earnings in period t, $\mathbf{X}$ is a vector of observable pre-and post displacement worker-, plant-, and labour market-characteristics, $EXIT_{i,t-j}$ is a dummy variable indicating whether worker separated from a plant at time the closure occurred, $t-j$, and $EARLY_{i,t-j}$, is a dummy variable indicating whether worker separated at time $t-j$ from a plant that died at time $t+1-j$. The full set of displacement dummies, $D_{i,t-j}$, $j = -m, -m+1, 0, ...k$ indicate that job loss is allowed to affect the outcome m years before its occurrence until k years after its occurrence[10]. As a comparison group we use workers in continuing plants. The vector of observables, $\mathbf{X}$, is assumed to capture both factors that affect the earnings in current year, and the factors that might influence the selection of worker's into different displacement categories. The specification might also include worker specific fixed effects, α_i, in order to control for the unobservable non-time-varying heterogeneity between workers[11].

In addition, we allow the effect of job loss depend on the fact whether worker moved directly to a new job or whether he experienced some unemployment spells at the time of separation. As described in section 3.2. we divide workers into 5 different categories according to their separations status: 1. job-to-job exit-layoffs., 2. not-job-job exit-layoffs, 3. job-to-job early-leavers, 4. not-job-to-job early-leavers, and 5. other workers. We estimate the effect of job loss on post-displacement earnings, and allow this effect to vary for four different displacement categories. Workers in the final group (5) are used as a comparison group.

5 Results

The results are reported in appendix. We begin by reporting descriptive information on workers in exiting and non-exiting plants. The sample consist of workers, who were employed in 1995 in plants that had survived from 1992 until 1995. Year 1995 is marked as year $t = 0$. Plants that exited between 1995 and 1996 are labeled as exiting plants.

[10] Various studies have found that the earnings of displaced workers start to decrease already in the years before the displacement occurs (e.g. Jacobson et al. 1993).

[11] Note however, that since our model compares exiting plant workers to non-exiting plant workers, when we include the worker specific fixed effects we can no longer identify the effect of "being an exiting plant worker" (or loosing a job in plant closure). The only way to do this, is to assume that the possible closure does not have effect on wages on the first observation year (t-3).

5.1 Effect of future closure on worker turnover

Table 2 describes the average worker characteristics of exiting and non-exiting plants in the sample in pre-exit years[12]. As expected, the results indicate that exiting plants are shrinking in pre-exit years. Their workforce seem to become older, and have more tenure as the closure approaches. The increase in average tenure and age is faster in exiting plants than in non-exiting plants. This might indicate that dying plants reduce recruiting before the closure and exiting workforce is thus getting older more rapidly than workforce in continuing plants. Compared with non-exiting plants, exiting plants are in average smaller, employ in average younger workers, and workers with less tenure and education. The smaller tenure (and average age) might indicate that these plants are in average younger than non-exiting plants. The exiting plants also employ less females, and less married people.

In order to look whether the future closure affects workforce skill distribution, we match the *plants* from the 1995 base year sample to the information of their *workers* in different pre-exit years. The variables that are used to describe worker quality or skills are: worker's age, years of schooling, tenure, and logarithm of annual earnings. Table 3 reports the mean, and 0.1, 0.5 and 0.9 percentiles of these variables for exiting and non-exiting plant workers in different pre-exit years. Table also shows the difference in the level and growth of these measures between exiting and non-exiting plant workers. The idea is to look whether the distribution of worker characteristics differs significantly between exiting and non-exiting plants, and whether the distribution changes significantly as the closure approaches.

Table 3 shows that workers in exiting plants are in average younger than non-exiting plant workers in all pre-exit years. Surprisingly, the workforce in exiting plants seems to become in average slightly younger as the closure

[12]This table is produced using plant-level data. That is, we match the information on the 1995 base sample plants with the information of these plants' average worker characteristics in different pre-exit years.

approaches[13]. This might be driven by the possibility that the oldest workers separate (e.g. to retirement) from these plants, since the difference holds only in the higher tail of the age distribution. Workers in exiting plants seem to have in average less education than workers in non-exiting plants. The difference becomes stronger as the closure approaches even tough the average level of schooling in exiting plants slightly rises. There is an increase in average tenure of exiting plant workers just before the closure occurs. This indicates that during the period just before the closure, i.e. between -1 and 0, the low tenure workers are more likely to leave.

Final rows report the level and the difference of annual earnings of workers in exiting-and non-exiting plants in different pre-closure years. Surprisingly, it seems that in our sample the workers in exiting plants earn in average more than workers in non-exiting plants. In addition, their wage growth during the whole period (from -3 to 0) is stronger than that of non exiting plant workers. However, when comparing the earnings growth just before the closure, i.e. between years -1 and 0, the earnings of exiting plant workers grow less rapidly than those of non-exiting plant workers. This might indicate either that the shock that leads to the closure affects workers earnings in these plants, or that the workers with higher wages (and productivity) leave from these plants just before the closure. Lower earnings of exiting plants in the year just before closure might also be explained by the possibility that the closure occurs already in the end of that year and thus affects the average annual earning.

By looking at the changes in average worker characteristics within plants, we cannot know whether these changes reflect changes in the characteristics of existing workforce or whether the possible firm death changes firm's recruitment policies and workers' leaving probabilities. Next we study whether

[13]It is important to note that this results differs from the result with plant level data in table 2. One reason for the difference might be that the averages in table 1 are weigted by number of plants, not by number of workers. The results also differ significantly from the results in section 5.2., which indicate that the stayers in exiting plants are in average older than the leavers.

the composition of separators from plant change before the closure occurs. Table 4 reports average characteristics of stayers and separators in exiting and non-exiting plants in different pre-exit years. Separators from both exiting and non-exiting plants are in average younger and have less tenure. Consequently (perhaps) their earnings are at lower level than the earnings of the workers who stay with they employer that period. Separators seem to be slightly more educated than stayers, and this difference is bigger for exiting plant workers. Interestingly, workers who stay with the plant until the end, i.e. workers who leave the plant at the period (t-0) when the closure occurs, are younger and slightly more educated than stayers of these plants in earlier periods. This indicates that the dying plant is recruiting younger and more educated workers just before the closure occurs.

Next we examine in more detail whether workers who leave the dying plant in the period before closure (t-1) occurs differ by their observable characteristics from the stayers. Table 5 reports the average characteristics of the workers in different separation categories in the year t-1. The exiting plant workers are workers whose plant closed down between t and t+1. Stayers stayed with these plants until the period t (i.e. did not separate between t-1 and t). Early-leavers left from these plants between t-1 and t. The results indicate that there are significant differences in the observable characteristics of these workers. Exiting plant workers are younger and have less tenure and education than non-exiting plant workers. They also have higher wages but slower wage growth. They come from bigger labour markets, are more often males and less likely to be married than non-exiting plant workers.

Compared with other workers in exiting plants, workers who stay with their plant until the end, *stayers*, are significantly older and have more tenure. They also have in average higher earnings and higher wage growth. This is consistent with the hypothesis that these workers have significantly more firm-specific human capital. In addition the stayers have slightly less schooling and they are more likely to be married. They also come from slightly smaller labour markets than the workers who separate from the dying plants before the closure occurs, which might indicate that they have smaller changes of getting job offers while on-the-job.

Within the *early-leavers* category, the ones who are more likely to move voluntarily, *job-to-job movers*, are younger, have more tenure, more education and are more likely to be married than *not-job-to-job movers, i.e.* the workers who were more likely to be laid-off during the period. In addition, the job-to-job movers have higher earnings but lower earnings growth. They also come from bigger labour market. All these factors are consistent with the expectation that worker's decision to leave voluntarily from a dying plants is related to his outside opportunities, i.e. to the probability of receiving a wage offer while still on-the-job.

Next we examine how much these factors affect the probability of being in different layoff categories. Table 6. reports the estimation results of a standard probit model. First columns explains the factors that affect the probability of being an exiting plant worker. The results indicate that exiting plant workers are slightly older, have less tenure, less education, are less likely to be married, and are more often males than similar workers in the same industry and labour market. They also seem to have higher wages than similar workers in the same industry and labour market. It also seems that once taken into account the other observable characteristics, workers in labour market with higher unemployment rate are less likely to work in exiting plants. This is a bit puzzling result, but it is important to remember that but this information is from year t-1, while exit occurs between t and t+1.

Next columns report the probability of leaving an exiting plant in period before its closure occurs[14]. The sample used in the estimation consists now only of the exiting plant workers, and thus we estimate the probability of

[14]This group is likely to consists both of the voluntary movers and of the workers who were laid off during this period. One way to distinguish between these two groups is by separating this category to job-to-job movers and not-job-to-job movers.

separating from a dying plant in the period before the closure occurs, conditional on being an exiting plant worker. The results show that worker is more likely to separate from an exiting plant if he is younger and have less tenure. This might indicate that these workers have less firm specific human capital and are thus willing to search more intensively for new jobs. Workers working in exiting plants located in labour market with high unemployment rate are less likely to separate early. This makes sense since these workers are less likely to get offers from prospective employers. Wage or wage growth seem to have negative but not significant effect on the leaving probability.

5.2 Post-displacement earnings losses

In the final part of the empirical analysis we estimate an earning regression (4) to evaluate the effect of displacement that results from plant closure on pre- and post-displacement earnings. The coefficient on displacement effect is allowed to vary by displacement categories. Table 7 reports the results of the earnings regressions, where workers are divided into two categories according to their separation status: *exit-layoffs* and *early-leavers*. The first column in table 7 reports the results of pooled OLS regression. The reported coefficients belongs to a dummy variable that indicates displacement that occurs between t and t+1. The displacement that occurred between t and t+1 is allowed to affect workers earnings from periods t-3 to t+3. The model controls for age, age squared, education, gender (female dummy), marital status, pre-displacement job tenure, plant size, and for the size of local labour market. In addition the specification includes dummies to control for fixed time, industry and regional effects.

The estimation results imply that there are significant differences in the post-and pre-displacement earnings of workers who leave dying plant in different stages. Compared with similar workers in the same industry and labour market the earnings of workers who were laid off in plant closings between t and t+1, *exit-layoffs*, are actually at higher level in all pre-and post-displacement years. On the other hand, *early-leavers* from dying plants, i.e. workers who separated during this period (between t and t+1) from plants that die in the next period (between t+1 and t+2), earn significantly less than similar workers in continuing plants in the same industry and same labour market. This might indicate that the early-leavers group consists mainly of "lemons", i.e. of those who are kicked out first when the plant gets into trouble.

It might be, however, that these differences in earnings are not due to workers displacement status, but on some other (unobservable) characteristics that might affect the selection into different displacement categories. In order to control for such heterogeneity between different type of workers we estimate the model with individual-specific fixed effects. We use the earnings in year t-3 as the comparison year, and thus drop this years displacement dummy from the regression. This is necessary since the model compares workers who were displaced in plant closure to workers who were not displaced in plant closure, and thus the displacement effect could otherwise not be identified when the worker fixed effects are introduced. It is important to note, however, that the model relies on assumption that earnings at t-3 are not influenced by the future displacement event[15].

The results indicate that when controlling for the unobservable heterogeneity, it seems that workers who stay with their plant until the end, *exit-layoffs*, suffer significant earning reductions after the displacement, while no such observation is found for *early-leavers*. Contrary to pooled OLS results, this indicates that the early-leavers group consists mainly of voluntary early-leavers and not of layoffs.

In order to distinguish between these two groups we divide the displacement categories to two subcategories: *job-to-job movers* and *not-job-to movers* as described in section 3.2. Job-to-job movers are assumed to

[15] The period t-3 means that the actual displacement will occur 3 to 4 years from that moment. Jacobson et al. (1993) find out that earnings do not start to decrease earlier than 3 years before the actual closing down occurs.

separate voluntarily from these plants, while the not-job-to job movers are more likely to be laid-off. Table 8 reports the estimation results of earning regression where the displacement effect is allowed to vary between all these categories. The upper panel reports the results of OLS regression without individual-specific fixed effects. As expected, the workers who loose their jobs in plant closings and manage to move directly to new jobs seem to be no worse off than similar workers in continuing plants. This holds for both the *exit-layoffs* and for the *early-leavers*. On the other hand, workers who experience some unemployment around displacement are clearly worse off than workers in continuing plants. The negative effect is much stronger for workers who were laid off in the period before the closure occurs. This might indicate that these workers are of lower quality, and that there are some unobservable factors that explain their lower earnings capacity.

The lower panel in table 8 report the results of fixed effects regressions. The result indicate now that workers who loose their jobs in the period when the closure occurs suffer some post-displacement earnings reductions regardless of the fact whether their move directly to new jobs or not. For early-leavers the results are very clear: the ones who manage to move to new jobs directly, i.e. the voluntary early-leavers, suffer no earning reductions in their post-displacement jobs, while workers who do experience some unemployment around displacement suffer significant post-displacement job losses. This indicates, that there is significant heterogeneity between workers who separate the dying plants during the period before the closure. Workers who stay with the dying plant until the end are more homogenous group of workers.

To sum up, the results are consistent with the theoretical predictions. Workers who voluntarily leave the dying plant in the period before the closure occurs do not suffer any earnings reductions in their post-displacement jobs. Moreover, workers who were laid off in the period before the closure occurs, suffer much more severe earning reductions than workers who were laid off during the period when the plant was shut down.

6 Conclusions

This paper had two objects. First, we wanted to examine whether there is a selective turnover of workers in dying plants before the closure. The hypothesis is that the knowledge of future economic distress will influence both firm's hiring and firing decisions, as workers' quitting decisions. This is assumed to change the workforce skill distribution within firms. Second, we aimed to examine whether this selection process implies that there are differences in the re-employment wages of the workers who leave the firm in different stages. The results using matched employer-employee panel data from Norway are consistent with the theoretical predictions. Workers who decide to leave the dying plants early suffer no wage losses in their re-employment jobs, while the ones who stay until the end suffer significant earning losses. On the other hand, workers who are laid off in the period before the plant's death suffer even more severe earnings reductions, than the ones who were laid off during the period when the closure occurred.

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A Appendix

A.1 Notification rules in Norway

The general notification time before laying off people in Norway is 1 month. However, this depends on the tenure in the job. For workers with more than 5 year tenure it is 2 months and for workers with more than 10 year tenure it is 3 months or more depending on age. It is 4 months if the worker is older than 50 year, 5 months if the worker is older than 55 year and 6 months if the worker is older than 60 year. People can be laid off immediately if for a strong cause (serious misbehavior) or with 2 week notice if the firm has to close due to a disaster like fire. Workers can be laid off temporarily with 2 week notice.

APPENDIX TO SECTION V

Table 1 Information on the 1995 sample

	Number of plants at t=0	Percent	Number of workers at t=0	Percent
Non-exitors	7 206	94.55	116 227	96.49
Exitors	415	5.45	4 226	3.51
Total	7 621	100	120 453	100

Table 2 Descriptive information of the average characteristics of exiting and non-exiting plants in the pre-exit years

Time	-3	-2	-1	0
Exiting plants				
Plant size	13.02	11.86	11.87	10.18
Average age	38.68	39.36	39.95	40.84
Average tenure	4.68	5.26	5.68	6.26
Average years of schooling	10.80	10.87	10.92	10.94
Share of females	0.45	0.45	0.43	0.42
Share of married	0.55	0.54	0.55	0.54
Non-exiting plants				
Plant size	16.07	16.04	16.41	16.13
Average age	39.43	39.87	40.14	40.39
Average tenure	5.23	5.68	6.04	6.38
Average years of schooling	10.98	11.03	11.09	11.15
Share of females	0.47	0.47	0.47	0.47
Share of married	0.59	0.59	0.58	0.57
Difference between exiting and non-exiting plants				
Plant size	-3.04	-4.18	-4.55	-5.95
Average age	-0.76	-0.51	-0.19	0.45
Average tenure	-0.55	-0.42	-0.36	-0.12
Average years of schooling	-0.19	-0.17	-0.18	-0.21
Share of females	-0.03	-0.02	-0.04	-0.05
Share of married	-0.04	-0.05	-0.03	-0.03

Table 3 Mean and 0.1, 0.5 (median), and 0.9 quantiles of main variables from pre-exit years for exiting and non-exiting plant workers

Exiting plant workers Variable:		Exiting plant workers Mean	0.1	0.5	0.9	Non-exiting plant workers Mean	0.1	0.5	0.9	Difference btw. exiting and non-ex. Mean	0.1	0.5	0.9
Age													
Time	-3	38.96	24	37	57	40.05	24	39	58	-1.09	0	-2	-1
	-2	39.08	24	38	57	40.29	24	40	58	-1.21	0	-2	-1
	-1	38.83	24	37	56	40.30	24	40	57	-1.48	0	-3	-1
	0	38.76	24	38	56	40.33	24	40	57	-1.57	0	-2	-1
Difference from	-3 – 0	-0.20	0.00	1.00	-1.00	0.28	0.00	1.00	-1.00	-0.48	0	0	0
	-1 – 0	-0.07	0.00	1.00	0.00	0.03	0.00	0.00	0.00	-0.09	0	1	0
Education													
Time	-3	11.07	8	11	14	11.32	8	11	15	-0.25	0	0	-1
	-2	11.12	8	11	14	11.41	8	11	15	-0.29	0	0	-1
	-1	11.15	8	11	14	11.49	8	11	16	-0.34	0	0	-2
	0	11.21	9	11	14	11.54	9	11	16	-0.32	0	0	-2
Difference from	-3 – 0	0.14	1.00	0.00	0.00	0.21	1.00	0.00	1.00	-0.07	0	0	-1
	-1 – 0	0.06	1.00	0.00	0.00	0.05	1.00	0.00	0.00	0.02	0	0	0
Tenure													
Time	-3	5.07	0	4	12	5.93	1	4	14	-0.86	-1	0	-2
	-2	5.04	0	4	13	6.17	1	5	15	-1.13	-1	-1	-2
	-1	5.00	0	3	13	6.31	1	5	16	-1.31	-1	-2	-3
	0	5.38	0	3	14	6.53	1	5	17	-1.15	-1	-2	-3
Difference from	-3 – 0	0.32	0.00	-1.00	2.00	0.60	0.00	1.00	3.00	-0.28	0	-2	-1
	-1 – 0	0.38	0.00	0.00	1.00	0.22	0.00	0.00	1.00	0.16	0	0	0
log(Wage)													
Time	-3	12.11	11.26	12.27	12.87	12.08	11.32	12.23	12.74	0.03	-0.06	0.04	0.13
	-2	12.13	11.32	12.27	12.84	12.09	11.33	12.23	12.74	0.05	-0.01	0.04	0.10
	-1	12.17	11.40	12.31	12.86	12.11	11.35	12.25	12.75	0.07	0.05	0.06	0.10
	0	12.16	11.42	12.29	12.82	12.13	11.39	12.27	12.78	0.03	0.03	0.02	0.04
Difference from	-3 – 0	0.05	0.16	0.01	-0.05	0.05	0.07	0.04	0.04	0.00	0.09	-0.02	-0.09
	-1 – 0	-0.01	0.02	-0.02	-0.04	0.03	0.04	0.02	0.02	-0.04	-0.02	-0.04	-0.06

Table 4 Average characteristics of workers in exiting and non-exiting plants according to separation status in different pre-exit years

	Exiting plant workers		Non-exiting plant workers	
Period/Variable:	**Stayers**	**Separators**	**Stayers**	**Separators**
t-3				
Age	39.70	37.05	41.01	36.06
Education	10.95	11.37	11.31	11.38
Tenure	5.66	3.55	6.39	4.03
Log. wage	12.15	12.02	12.16	11.76
t-2				
Age	39.44	38.01	41.13	36.35
Education	11.08	11.25	11.39	11.49
Tenure	5.47	3.78	6.68	3.84
Log. wage	12.18	12.00	12.16	11.74
t-1				
Age	39.77	37.20	41.28	36.89
Education	11.09	11.24	11.42	11.73
Tenure	5.86	3.52	6.88	4.33
Log. wage	12.22	12.10	12.18	11.84
t-0				
Age		38.76	41.62	36.87
Education		11.21	11.49	11.65
Tenure		5.38	7.26	4.57
Log. wage		12.16	12.20	11.95
Age		38.76	41.62	36.87

Table 5 Average characteristics of workers in exiting and non-exiting plants according to separation status

	Exiting plants					Non-exiting plants
	All	Stayers	(Early)-Leavers			All
		All	All	Job-to-job	Not-job-to-job	
Age	38.83	39.77	37.20	36.86	37.66	40.30
Tenure	5.00	5.86	3.52	3.63	3.37	6.31
Education	11.15	11.09	11.24	11.35	11.09	11.49
Female (=1)	0.36	0.35	0.38	0.34	0.43	0.49
Marital status	0.50	0.53	0.45	0.50	0.39	0.58
Earnings at t=-1	236329	243884	223366	253913	181707	213837
Earnings at t=-2	222429	231179	207432	230526	176018	203693
Earnings at t=-3	204713	209430	196584	220262	163902	191872
Earnings growth btw -2 -1	0.33	0.33	0.33	0.32	0.34	0.36
Av. Earn. growth btw -3 -1	0.37	0.39	0.35	0.22	0.52	0.38
Region unemp. rate	0.03	0.03	0.03	0.03	0.03	0.03
Size of l. market	139227	133084	149768	176652	113105	116433
0bservations	4924	3111	1813	1046	767	118273
%	100.00	63.18	36.82	21.24	15.58	

The information on the average characteristics are from year -1 (1994). Exiting plant workers are workers who worked in 1994 at plant that exited btw 1995 and 1996. These workers are divided into stayers and early-leavers. Early-leavers are the workers who separated from these plants in previous period, i.e. btw. 1994 and 1995. Note, the new hires by exiting plants btw 1994 and 1995 are not in this figure. This is why the number of exiting plant workers does not sum to 4226 (100%) which is the number of exiting plant workers in 1995. These include stayers, 3111 (73.62%) and number of new hires 1115 (26.38%).

Table 6 The effect of different pre-displacement characteristics on the probability of being an exiting plant worker and on the probability of leaving the exiting plant in the period before the closure occurs.

Variable:	**Probability of being exiting plant worker**				**Early-leaving probability for exiting plant workers**			
	dF/dx	Std. Err.	z	P>z	dF/dx	Std. Err.	z	P>z
Age	0.004	0.005	0.71	0.475	-0.307	0.089	-3.46	0.001
Tenure	-0.002	0.000	-14.56	0.000	-0.016	0.002	-7.67	0.000
Education	-0.002	0.000	-8.14	0.000	0.001	0.004	0.30	0.765
Married*	-0.004	0.001	-3.76	0.000	-0.009	0.018	-0.53	0.599
Female*	-0.015	0.001	-12.31	0.000	-0.008	0.020	-0.41	0.683
Log(wage) at 94	0.005	0.001	5.13	0.000	-0.011	0.015	-0.78	0.433
Wage change 94-93	0.000	0.000	-0.20	0.841	0.000	0.002	0.02	0.984
Local unemp. Rate	-0.132	0.083	-1.59	0.111	-8.553	1.531	-5.59	0.000
Size of local l.market	0.000	0.000	13.02	0.000	-0.307	0.089	-3.46	0.001
2-digit ind dummies	Yes				Yes			
Number of observations	106217				4200			
LR chi2	2941.59				1149.37			
Pseudo R-sq.	0.0831				0.2287			

ML-probit marginal effect estimates. These are two separate probit regressions. The latter one is estimated using only the sample of exiting plant workers (for which information on relevant pre-dpl. characteristics could be found). The variables are from year t-1, while exit occurs between t and t+1.

Table 7 Effect of job displacement that results from plant closure on post-and pre-displacement earnings

	Model 1 (pooled OLS) Type of displacement:				Model 2 (Fe) Type of displacement:			
Effect displacement	Exit-layoff		Early-leaver		Exit-layoff		Early-leaver	
on wages at:	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Pre-displacement years:								
t-3	0.059	(0.014)	-0.055	(0.028)				
t-2	0.072	(0.013)	-0.057	(0.027)	0.003	(0.012)	0.004	(0.025)
t-1	0.092	(0.011)	-0.063	(0.023)	0.014	(0.012)	-0.004	(0.025)
t-0	0.099	(0.010)	-0.028	(0.019)	0.014	(0.012)	0.021	(0.025)
Post-displacement years:								
t+1	0.075	(0.011)	-0.054	(0.024)	-0.016	(0.012)	-0.011	(0.025)
t+2	0.074	(0.013)	-0.029	(0.029)	-0.027	(0.012)	-0.006	(0.025)
t+3	0.052	(0.013)	0.023	(0.030)	-0.051	(0.012)	0.035	(0.025)
Individual fixed effects	No				Yes			
Industry fixed effects	Yes				No			
Region fixed effects	Yes				Yes			
Year fixed effects	Yes				Yes			
R-sq	0.358				0.147 (within)			
Observations	795094				795094			

The data are a balanced panel of workers for years 1992-1998. The dependent variable is ln(annual earnings). The following control variables are included, but not reported: Age, age squared, regional rate of unemployment, time and area dummies. The model 1 controls also for sex, marital status and various pre-displacement characteristics such as: job tenure, plant size, size of the local labor market. The coefficient belongs to a dummy variable that indicates displacement that occurs between t and t+1. The coefficient is allowed to vary by type of displacement.

Table 8 Effect of job displacement that results from plant closure on post-and pre-displacement earnings for job-to-job movers and not-job-to-job movers

Model 1 (pooled OLS)	Exit-layoff				Early-leaver			
Type of displacement:	Job-to-job		Not-job-to-job		Job-to-job		Not-job-to-job	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
t-3	0.143	(0.014)	-0.097	(0.029)	0.032	(0.031)	-0.167	(0.049)
t-2	0.149	(0.013)	-0.073	(0.026)	0.072	(0.026)	-0.222	(0.051)
t-1	0.160	(0.010)	-0.030	(0.022)	0.005	(0.028)	-0.148	(0.039)
t-0	0.141	(0.010)	0.026	(0.019)	0.032	(0.022)	-0.103	(0.033)
t+1	0.146	(0.011)	-0.057	(0.024)	0.098	(0.021)	-0.259	(0.046)
t+2	0.147	(0.012)	-0.070	(0.028)	0.143	(0.025)	-0.275	(0.057)
t+3	0.102	(0.014)	-0.044	(0.028)	0.149	(0.031)	-0.162	(0.057)
Individual fixed effects	No							
R-sq	0.359							
Observations	795094							
Model 2 (Fe)	Exit-layoff				Early-leaver			
Type of displacement:	Job-to-job		Not-job-to-job		Job-to-job		Not-job-to-job	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
t-3								
t-2	-0.006	(0.015)	0.019	(0.020)	0.041	(0.033)	-0.045	(0.038)
t-1	-0.011	(0.015)	0.061	(0.020)	-0.029	(0.033)	0.024	(0.037)
t-0	-0.035	(0.015)	0.107	(0.020)	-0.013	(0.033)	0.061	(0.037)
t+1	-0.029	(0.015)	0.010	(0.020)	0.054	(0.033)	-0.103	(0.038)
t+2	-0.028	(0.015)	-0.028	(0.021)	0.099	(0.033)	-0.160	(0.039)
t+3	-0.068	(0.015)	-0.018	(0.021)	0.102	(0.033)	-0.065	(0.040)
Individual fixed effects	Yes							
R-sq (within)	0.147							
Observations	795094							

The data are a balanced panel of workers for years 1992-1998. The dependent variable is ln(annual earnings). The following control variables are included, but not reported: Age, age squared, regional rate of unemployment, time and area dummies. The model 1 controls also for sex, marital status and various pre-displacement characteristics such as: job tenure, plant size, size of the local labor market. The coefficient belongs to a dummy variable that indicates displacement that occurs between t and t+1. The coefficient is allowed to vary by type of displacement.