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Causes and labor market consequences of producer heterogeneity

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Abstract

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This thesis consists of four self-contained essays.

Essay I studies establishment-level employment changes in the Swedish Manufacturing sector over the 1972-96 period. The results show that modest changes in the aggregated employment record have been the resulting sum of rather large gross flows of jobs and that this constant reshuffling of jobs has important implications for the workforce and is closely related to process of economic growth. Shifts in employment across industries or other observable characteristic of establishments cannot explain the different employment outcomes across establishments.

Essay II (with A. Vejsiu) studies the determinants of plant closures in Swedish Manufacturing. From our theoretical framework we derive and empirically test hypotheses regarding the linkages between the probability of plant failure and industry-specific characteristics; local labor market conditions; and plant-specific sources of heterogeneity, including insider mechanisms in wage determination, plant specific human capital, selection mechanisms and technology vintage effects. Our results suggest that all these factors matter in ways that by and large conform to the *a priori* hypotheses.

Essay III investigates the importance of access to product markets in explaining the spatial wage distribution by estimating the parameters of a spatial labor demand model. The model takes into account the effects of sorting of heterogeneous labor and heterogeneity in transportation costs. The results are consistent with the idea that increasing returns to scale together with transportation costs is an important driving force behind urban agglomeration and sizeable spatial wage differentials.

Essay IV (with H. Holzer and J. Lane) presents a dynamic analysis of workers who persistently have low earnings over a period of three or more years. Some of these workers manage to escape from this low-earning status over subsequent years, while many do not. We analyze the characteristics of persons and especially of their firms and jobs that enable some to improve their earnings status over time.

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This thesis is the product of several years of research at the University of Uppsala, the Institute for Labor Market Policy Evaluation (IFAU) in Uppsala and the U.S. Census Bureau's Longitudinal Employer-Household Dynamics Program (LEHD) in Washington, D.C. I owe thanks to a great number of people at each of these places.

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I would like to express my gratitude to Susanne Ackum-Agell and all her staff for giving me the opportunity to work in such an intellectually and socially stimulating environment as IFAU.[2]

About two years ago, during a period when progress was slow, I received a phone call from Julia Lane that would change a lot of things in my life. Julia asked me to come to Washington, D.C., and join the LEHD team at the U.S. Census Bureau. In spite of "Scenic Suitland", the many long hours and involvement in way too many projects, this has been a truly great experience in every way and as Julia would put it "there is never a dull moment at LEHD!" I thank Julia for giving me this great opportunity, and for being such a great colleague, mentor and friend. John Abowd, John Haltiwanger and the rest of the staff also deserve a lot of recognition for

[1] Anders' qualities as a friend is perhaps best demonstrated by the fact that he and his family agreed to adopt my two cockatiels when I moved to the United States, in spite of being fully informed about their peculiar behavior. I suspect, however, that they get along pretty well, given that Anders and Clemens share the same taste for red wine.

[2] I am especially moved by the engagement of everyone at IFAU in the "search-and-rescue operation" when I arrived a day later than expected from abroad (I still claim that I said that I would be gone for *approximately*, and not *exactly*, 14 days).

making LEHD such a great place to work.

I have had the privilege to work with a number of great coauthors over the years and I appreciate everything I have learned from you. Apart from Julia they include Simon Burgess, Harry Holzer, Erica McEntarfer, Julia Lane and Altin Vejsiu.

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Most of the burden of writing this thesis, however, has fallen on the one person closest to me. Therefore, Lotta, more than anyone else I thank you for all your support, patience and love.

Washington, D.C., April 2003

Fredrik Andersson

Introduction

The common denominator of the four essays in this thesis is the usage of longitudinal micro data to study the empirical importance of producer heterogeneity in the labor market. Traditionally the importance of differences across firms and establishments has been a neglected area in empirical labor economics. However, as new kinds of datasets have been created, making it possible to study the dynamic interaction between workers and firms, a growing body of literature now suggests that the effects of firm heterogeneity on various labor market outcomes are substantial. For instance: Abowd and Kramarz (1999) show that a large fraction of the variation in individual earnings can be attributed to factors associated with firms rather than workers; Davis and Haltiwanger (1999) and Burgess, Lane, and Stevens (2000) are examples of studies that show that the importance of firm heterogeneity to explain worker mobility; Baily, Hulten, and Campell (1992) and Foster, Haltiwanger, and Krizan (2001) are examples of studies that show the relationship between firm heterogeneity and macro economic outcomes, by relating aggregate productivity growth to its micro foundations. The essays that form this thesis are closely related to this literature.

Essay I documents and studies the extent and importance of heterogeneity in plant-level employment outcomes in Swedish Manufacturing. *Essay II* and *Essay III* look at some of the causes of producer heterogeneity. In particular: The motivation for *Essay II*, which examines the determinants of plant closures, is based on one of the key findings in *Essay I*, namely that plant turnover contributes substantially to economic growth. *Essay III* investigates the empirical relevance of a spatial labor demand model, which hypothesizes that differences in product market access contribute to explain differences in firm-wage premia across establishments. *Essay IV*, finally, studies the importance of producer heterogeneity for dynamics in the low-wage labor market. Even though the links between the four essays are obvious, the differences between them are such that it makes more sense to discuss them individually in the following sections.

Job Flows in Swedish Manufacturing

Ever since the seminal work of Davis and Haltiwanger (see e.g. Davis, Haltiwanger, and Schuh, 1996)[3] a large number of papers have been published that document the job flow process in different countries and sectors of the economy. *Essay I* is part of this tradition by presenting an analysis of the extent, causes and consequences of the job flow process in Swedish Manufacturing, based on data that make comparisons with results for U.S. Manufacturing meaningful.

The results show that modest changes in the aggregated net employment record is the resulting sum of a tremendous heterogeneity in the employment dynamics at the micro level and that these differences across plants tend to increase in economic downturns. Several pieces of evidence are presented indicating that much of the burden of reallocating jobs inevitably falls upon workers, as job flows induce workers to switch employers and shuffle between employment and joblessness. However, there are also significant returns to this process, as the reallocation of labor from less to more productive producers plays an important role in the economic growth process.

These general results are quite similar to the results obtained for U.S. Manufacturing. However,the average pace of job reallocation has been considerably slower than in U.S. Manufacturing. A tentative explanation for the discrepancy between Swedish and U.S. Manufacturing with respect to the average pace of job reallocation could be made in terms of presumably larger adjustment costs in the Swedish economy.

Motivated by the consequences for the individual concerned and the importance for the economic outcome, the paper investigates into the driving forces of why jobs are created and destroyed simultaneously and what causes the pace of job reallocation to vary over time. The hypothesis that the heterogeneity is the resulting sum of cross-sectional variation in the employment outcome is strongly rejected. Instead, the heterogeneity of the plant-level employment outcome is a pervasive phenomenon even within narrowly defined sectors of the Manufacturing sector. Neither do aggregate and sectoral shift stories have any greater success in explaining why the job reallocation varies over time.

Most of these findings are in accordance with models that acknowledge growth and adoption of new technology as a noisy process, filled with experimentation and uncertain outcomes (e.g. Mortensen and Pissarides, 1994; Ca-

[3]Even earlier American studies include Leonard (1987) and Dunne, Roberts, and Samuelson (1989)

ballero and Hammour, 1994).

What are the Driving Forces of Establishment Turnover?

In spite of their many important consequences, as partly documented in *Essay I*, the knowledge about the driving forces of plant turnover is quite scarce. In *Essay II* we approach this issue by deriving and testing various hypotheses about the determinants of plant exit from a simple theoretical framework. The model contains links between the likelihood of plant failure and industry-specific characteristics of production and product demand, local labor market conditions as well as plant-specific factors. In particular any effects from the latter factors are interesting, since they can contribute to the understanding of why firms within industries and regions experience such different outcomes.

Our empirical findings based on longitudinal employer-employee data for plants in Swedish Manufacturing conform by and large to the hypotheses derived from the theoretical model. We find relatively strong effects on the plants' failure probability of the share of workers with some seniority. According to the theoretical model, this is consistent with the expected effects of insider mechanisms in wage determination (Lindbeck and Snower, 1989). Apart from the effects of seniority we find, perhaps surprisingly, small effects of differences in the structure of human capital across plants.

Previous studies have also looked at the importance of selection mechanisms by studying the hazard rate with respect to plant age. We address this source of heterogeneity as well, but unlike most previous studies we also make an attempt to disentangle and empirically test the importance of plant and technology age. We find that both plant age and our measure of technology age have independent effects on the probability of plant failure, lending some support to hypothesis derived from the selection literature (e.g. Jovanovic, 1982; Pakes and Ericson, 1992) and the capital vintage literature (e.g. Solow, 1956).

What is the The Role of Location in Explaining Wage Differentials across Establishments?

The concentration of economic activities is one of the most striking features of the economic landscape. Agglomerated regions are also areas where wages are generally higher than elsewhere – Glaeser and Mare (2001) report a 33% wage premium for workers in cities – and in sharp contrast to basic economic theory, the spatial wage differences are not arbitraged away by either movements of workers or relocation of firms. *Essay III* studies the forces of urban agglomeration that make the spatial wage differences persist over time.

I estimate a spatial labor demand model derived from the model of Krugman (1991) and Helpman (1998). The main idea of the model is that urban agglomeration arises as a result of increasing returns to scale in combination with the existence of transportation costs. Unlike previous studies I use micro data on the firm-wage premia for establishments to test the empirical validity of the theoretical model. There are at least two advantages with this approach. First, micro data help separate out any effects on firm-level wages from, on the one hand, the "market potential" of a location and, on the other, the direct and indirect effects of spatial sorting of workers with respect to their human capital. Another advantage is related to the fact that by using micro data, certain assumptions that transportation costs and production parameters are uniform across firms can be relaxed.

I obtain results that are consistent with the idea that the structure of the spatial wage distribution and urban agglomeration are at least partly the result of increasing returns to scale in production together with the existence of transportation costs. Interpreted literarily the estimates suggest that average prices are about 10-15% higher than marginal costs. Accordingly, I find that spatial factors can account for a relatively large fraction of the variation in wage markups across firms. In addition the sorting of workers with respect to human capital contributes to spatial wage differentials, even though the firm-wage premia seem to be determined by market access, rather than any externalities associated with the local level of human capital. Furthermore, the estimates indicate that transportation costs are heterogenous across industries in a way that is consistent with how firms are sorted in the spatial dimension.

Interaction of Workers and Firms in the Low-Wage Labor Market

As welfare reform was implemented throughout the U.S. in the late 1990's, millions of low-wage female workers entered the labor market. Concerns have been raised not only about their ability to find employment, but also about the levels of wages and benefits that they earn and their potential for earnings growth over time (e.g. Committee for Economic Development, 2000; Strawn, Greenberg, and Savner, 2001). Indeed, these factors will be critical determinants of the extent to which low-wage women will be able to escape poverty and achieve economic self-sufficiency for themselves and their families. And these issues are clearly just as relevant to low-wage male workers as to their female counterparts.

Yet some very fundamental questions remain about workers in low-wage labor markets in the 1990's and beyond. Among these questions are the following:

- To what extent do low-wage workers experience enough earnings growth over time to "escape" their low-wage or poverty status?
- Do the processes by which workers escape low-wage status differ across demographic groups – especially by gender and race?
- How important is wage growth *within* jobs, as opposed to mobility *across* jobs and employers, for those who escape low-wage status?
- What characteristics of *employers* contribute the most to success in the low-wage market, and which workers are matched to these employers? How important is the quality of that *match* for achieving success in the low-wage market, as opposed to individual skills and other attributes?

Essay IV addresses these issues by presenting an analysis of workers who persistently have low earnings in the labor market over a period of three or more years. Some of these workers manage to escape from this low-earning status over subsequent years, while many do not. Using data from the Longitudinal Employer Household Dynamics (LEHD) project at the U.S. Census Bureau, we analyze the characteristics of persons and especially of their firms and jobs that enable some to improve their earnings status over time.

Overall, the main results of this analysis are as follows:

- A significant fraction of prime-age adults in the United States with regular labor force attachment have very low earnings (i.e., $12,000 per year or less) that persist over a period of at least three years;
- These low earnings are associated both with the individuals' own demographic characteristics (i.e., race/gender and where they were born) and many characteristics of the firms for which they work (i.e., industry, size, turnover and net employment growth rates, and firm wage premia);

- Of those with persistently low earnings, nearly half manage to escape this status in subsequent years, though earnings improve only partially for most of them (i.e., they continue to earn less than $15,000 in at least some years);

- Of those with persistently low earnings, white males enjoy the highest subsequent earnings gains and highest rates of "escape" from this status of any race/gender group, while blacks endure the lowest improvements;

- Job and industry changes are associated with large percentages of the observed improvements in earnings, though a significant fraction (i.e., roughly a fourth to a third) of all escapes from low-earning status also occur among those who stay on initial jobs;

- Most earnings improvements for low-earning women occur within the service sector – in areas such as financial services, health care and education - while a larger fraction of those for males occur in the "traditional industries" like construction, manufacturing, transportation and wholesale trade;

- Significant parts of the lower subsequent earnings of black and other (mostly Hispanic) males among initial lower earners are accounted for by their lesser access than white men to high-quality jobs;

- Improvements in earnings associated with successful job changes for these workers are largely due to improvements in the returns to experience and job tenure associated with the new jobs, and also to the better characteristics of the new firms for which they work – i.e., improvements in both the current levels of earnings and their rates of improvement over time; and

- Temporary work agencies are associated with lower pay for low earners while they work for them but higher subsequent wages and better job characteristics afterwards.

These findings have some important implications for the low-wage labor market. For one thing, *some degree of upward mobility for persistently low earners is certainly possible*, and in fact is being achieved – even if these improvements remain fairly modest in most cases. Also, there is *no single path* for achieving earnings growth. Job changes are important to many who achieve earnings improvements, though staying on the job also works in a significant percentage of cases.

A range of characteristics also seems to be associated with these good jobs – including not only firm wage premia (which are not observable to workers or labor market practitioners) but also industry, firm size, rates of turnover and employment growth (which are observable). Thus, it is useful to try placing low earners into high-wage sectors, firms with low turnover, and larger firms that provide job ladders and possibilities of upward mobility.

The strong results here for temp agencies suggest that these or other types of labor market intermediaries may play important roles in helping assist low earners transition to better job opportunities. The overall results also suggest a strong need to improve access to good jobs for many low earners - especially those who are not white males.

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Essay I

Job Flows in Swedish Manufacturing

Job Flows in Swedish Manufacturing*

1 Introduction

Modest changes in the aggregated net employment record is the resulting sum of a tremendous heterogeneity in the employment dynamics at the micro level. For instance, in their seminal book Davis, Haltiwanger, and Schuh (1996) report that in every year a large fraction of all jobs in U.S. Manufacturing are either created or destroyed.[1] If differences in employment outcomes at the micro level is abstracted from – by assuming representative agents for instance – important features of the dynamic labor market will remain undisclosed. For instance: The constant reshuffling of jobs induces a large fraction of the workforce to switch employers and shuffle between employment and joblessness. This process is also an important element in the process of economic growth, as labor is reallocated from less to more productive employers.

Motivated by the consequences for individuals as well as macro economic outcomes, this study asks the following core questions about the job reallo-

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[1] The book is partly based on results in Davis and Haltiwanger (1990), Davis and Haltiwanger (1992) and Davis, Haltiwanger, and Schuh (1996). Even earlier American jobflow studies include Leonard (1987) and Dunne, Roberts, and Samuelson (1989).

cation process:

1. What are the basic properties of the employment dynamics at the micro level;

2. what are the consequences of job flows on the workforce; and

3. what are the explanations for simultaneous job creation and job destruction?

In the quest for answers to these questions a quite different institutional setting in Sweden as compared to most other countries is acknowledged. For instance, the presumably larger adjustment costs and lower wage flexibility in Sweden – resulting from strong unions and strict employment protection laws – have been put forward in the literature as factors affecting the job reallocation patterns (e.g. Bertola and Rogerson, 1997; Garibaldi, 1998).

The results based on establishment-level data for the Swedish Manufacturing over the 1972-96 period show that the basic properties of the job reallocation process are quite similar to those in U.S. Manufacturing, to the extent that: *most jobs reallocation is in excess of what is necessary to accommodate any aggregated change in employment*; and *the importance of the heterogeneity in micro-level employment outcomes seems to increase in economic downturns*. On the other hand, a notable difference is that *the average pace of job reallocation has been slower in Swedish Manufacturing*, which lends some support to the idea that country-specific institutions can make a difference also in this context. (That the data sources are similar make the comparisons meaningful.)

In terms of the consequences of job flows for the workforce, the results show that a large fraction of worker flows coincide with job creation and job destruction, which suggests that *demand factors are important in explaining worker mobility*. That job flows are highly concentrated to establishments experiencing large employment changes and that job flows are persistent phenomena further emphasize this point.

While the structure of job flows imposes mobility requirements on the workforce, the results also indicate a close relationships between the reallocation of jobs and aggregate growth in productivity. Over the period of data, some 60 percent of the growth in productivity can be attributed to activities that include reallocation of labor. In particular, the rise in job reallocation rates in the 1990's was associated with an increased role for input reallocation in explaining the aggregate growth in productivity.

Finally, with respect to explanations for why establishments experience such different employment outcomes, the fundamental result is that there are no easily observable characteristics of employers, such as industry, location or productivity measures, that can explain the different employment outcomes. Nor can these factors explain why the intensity of job reallocation varies over time. Instead, *the results are consistent with explanations based on the idea that growth and technological adoption at the micro level is a complex and heterogeneous process*, filled with experimentation and surrounded by uncertain outcomes.

The remainder of the paper is organized the following way. The next section provides a background. Data, concepts and measurement issues are discussed in Section 3. Section 4 documents the basic facts about the job reallocation process. Section 5 highlights some of the consequences of job flows in terms of how they affect the workforce and their relationship to economic growth. Section 6 provides a systematical investigation of why establishments experience such different employment outcomes. Section 7, finally, summarizes the results.

2 Background

This section presents the net employment record in Swedish Manufacturing, discusses likely effect on the job reallocation process of Swedish labor market institutions and summarizes key findings from the previous literature.

2.1 The Net Employment Record

Figure 1 shows the annual employment record in Swedish Mining and Manufacturing over the 1972-96 period according to data from Manufacturing Statistics. From 1975, when employment peaked at a little bit more than 940,000, there was an ongoing negative trend until sometimes around 1984, when employment was stabilized at around 770,000. The severe crisis in the beginning of the 1990's struck especially hard in Manufacturing, which is manifested in the employment record with the three largest negative net changes occurring in three consecutive years between 1990 and 1993. Distributed over the three years, employment fell by more than 185,000 to less than 580,000 in 1993. In the 1993-96 period employment recovered somewhat; the largest positive net change over the period did in fact take place

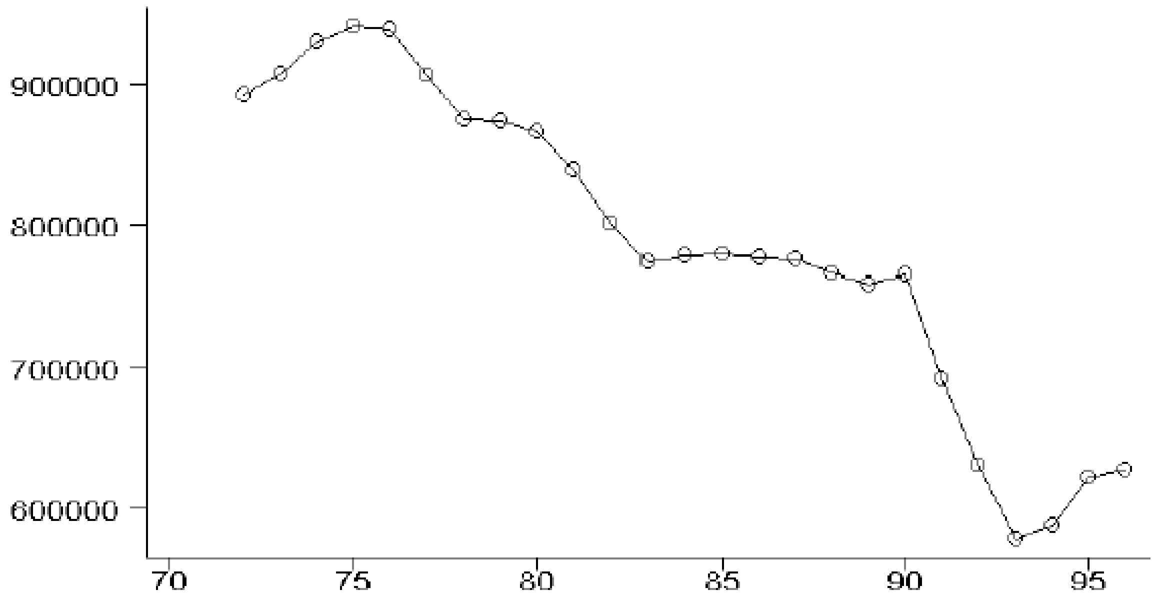

Figure 1: Employment in Swedish Manufacturing, 1972-96

between 1994 and 1995 when employment expanded by some 33,000.[2]

2.2 Institutional Setting and Previous Studies

There are country-specific institutions that might affect job flows that ought to be mentioned in this context: The Swedish Employment Security Act (*Lagen om Anställningskydd* or LAS), introduced in 1974, provides employees with extensive employment protection. Among other things, LAS stipulates the "first in, first out" principle in case of dismissals caused by redundancy. Furthermore, the probationary period before automatic tenure is a mere six months, which is very short by international standards.

The likely effect of LAS in particular and extensive employment protection in general is an increased wariness from the employer's side to react on a given disturbance, as the adjustment cost for doing so is high, resulting in less average job reallocation.[3] In addition the cyclical properties of

[2] The increase in employment in 1990 is partly an artifact of data (see Section 3.1), due to changes in the included population.

[3] As a result of the introuduction of LAS Agell and Lundborg (1993) finds evidence for

job flows could arguably be affected by extensive employment protection, an idea formalized by Garibaldi (1998). According to this model, extensive employment protection will increase the relative variability of job creation to job destruction and, thus, make job reallocation more procyclical. Boeri (1996) argues that countercyclical property of job flows is mainly a phenomenon found in the U.S., partly because of differences in employment protection in the U.S. and elsewhere.

If high adjustment costs were the only force at work, we would expect job flows to be relatively modest and less countercyclical in Sweden as compared to countries with presumably lower cost of adjustment. However, another feature of the Swedish economy is the large wage compression, institutionalized for many years by centralized wage negotiations and the so called "Swedish Model". An explicit aim of the "Solidarity Wage Principle" was to accommodate shocks in the economy by the reshuffling of jobs rather than adjusting wages.

In the mid-1980's, the system with centralized negotiations broke down and was replaced by a system with industry-level negotiations. Around the same time, as documented by Hibbs and Locking (2000), the dispersion in wages across individuals started to increase. In fact the increase has been the resulting sum of, not only increases in the wage dispersion between industries, but also increases in the wage dispersion within industries and establishments. Thus, if wage dispersion reflects the underlying wage flexibility, this could contribute to explain differences in job flows over time and as compared to other countries.

Quite surprisingly, given the presumption of large adjustment costs, but in accordance with the idea of large wage compressions, most European studies on gross job flows document job reallocation rates of the same order of magnitude or even higher than in the United States. Sweden is by no means an exception: In OECD (1994), the job reallocation rate of nearly 30 percent is, together with the corresponding rate for Morocco, the highest among the countries included.[4] The results from other job flow studies based on Swedish data, including Davidsson, Lindmark, and Olofsson (1994), Persson (1999) Andersson, Gustafsson, and Lundborg (1998) and Arai and Heyman (2000), are all quite different. These studies differ with respect to concept of an employer, quality of longitudinal links, the sector of the economy and

increased recruitment costs and a lower propensity to expand employment in economic upturns, and Holmlund (1978) finds that the hiring frequency decreased.

[4] Section 3 provides formal definitions of the various flow concepts. Loosely speaking a job reallocation rate of 30 percent implies that three out of every ten jobs either are created or destroyed during a year.

the time period covered, restrictions to the included population and so on. Therefore, rather than anything else more fundamental, the lesson from this is likely to be that it is notoriously difficult to compare results based on different data sources. For instance, as pointed out by Persson (1999), the data on reported job flows for the Swedish economy in the OECD study suffer form the inability to correctly follow the establishments longitudinally.

Throughout this paper references will be made to U.S. results, as reported by Davis and Haltiwanger (1992,1996,1999) using the Longitudinal Research Database (or LRD). This is done based on the argument that LRD and the Manufacturing Statistics – the data used in this study – share many important features and, thus, the scope of comparability should be relatively good. Another feature the two datasets have in common is the availability of rich economic and demographic information about each establishment, which is necessary to investigate into the driving forces of the employment dynamics at the micro level.

3 Data, Concepts and Measurement Issues

3.1 Data

Annual, plant-level data over the 1972-96 period from the Manufacturing Statistics (*Industristatistiken* or IS) produced by Statistics Sweden is used in this study. IS covers almost the universe of employment in the Manufacturing sector (Major SIC Divisions 10-37, which include Mining, Quarrying and Manufacturing); the included population is somewhat limited with respect to the smallest establishments. Altogether, the sample adds up to roughly 251,000 annual observations on 25,000 different establishments.

Each establishment is classified according to detailed industry, region and ownership (i.e. whether the establishment is owned by a firm with more than one establishment or not) and apart from employment data, information on sales, value-added, wages and a range of other costs are also available.

The ability to accurately trace the establishments longitudinally is crucial – the inability to do so will result in job flow estimates that are generally biased upward. Apart from the coverage, two other features of data enhance the quality: First, the nature of the establishment concept used in IS reduces the risk of spurious flows. The establishment is defined only in terms of its production and physical location, which implies that, for instance, changes in ownership would leave the identities of the establishments intact.

Second, IS has been linked to the Central Firm and Establishment Registry (*Centrala företags- och arbetsställeregistret*), which contains administrative data on the year of entry and (possibly) exit of each establishment. For instance, there were minor changes in the definition of the population of IS implemented in 1990. In short, non-manufacturing establishments within manufacturing firms were added (see various publications from Statistics Sweden for details). For the most parts these establishments were in existence prior to 1990 and, thus, should not be included in the set of entering firms in 1990. Access to adminstrative data on year of entry and exit make it possible to separate out real entries and exits from spurious ones caused by incomplete data and adjust the flow estimates. Apart from the effects of the changes in 1990, the adjustments do not affect any of the qualitative results, since the problem of incomplete data in IS affects very few observations.[5]

IS shares many important features with the LRD, including reliable longitudinal linkages of establishments, a quite similar establishment concept, coverage of the same sectors of the economy over more or less the same period. Another feature it shares with LRD is that the coverage of plants with fewer than 10 employees is not complete.[6] Because smaller establishments tend to be more volatile with respect to employment, the reported job flows measures are, therefore, somewhat biased downward. However, the effect from this is small.[7]

3.2 Measuring Gross Job Flows

Gross job flows are measured in terms of establishment-level employment deviations. Denote the level of employment at the establishment in year t

[5] Based on comparing job flows in the sample of plants included as a consequence of the changes in the population in 1990 with job flows in the total sample, it seems safe to conclude that the reported job flows are hardly affected by these changes.

[6] In comparison, the LRD does not contain plants with fewer than five employees and sample plants (with known sample weights) with fewer than 250 employees. See publications from Statistics Sweden for a complete description of the sampling procedure in IS and Davis, Haltiwanger, and Schuh (1996) for a description of the LRD.

[7] The estimate of the job reallocation rate is downward biased with at most 6 percent (or 0.7 percentage points at the average job reallocation rate). This, of course, is the sum of even smaller bias in the job creation and the job destruction rate estimates. In the bias calculation the following facts are considered: According to IS, no more than 8 percent of employment is concentrated in the non-included plants in any year. Since the non-included plats are more volatile, this number is an upper bound of the *average share* of employment in these plants over a year. The job reallocation rate among the non-included plants is about 1.8 times higher than in the sample average. This number is obtained from the results on the smaller plants that are included. This of course assumes that the non-included plants are not systematically different from the included small plants. There is nothing in the sampling procedure that contradicts this assumption and the relative difference in job reallocation rate is generally not contradicted by previous results.

with n_{et} and let $\Delta n_{et} = n_{et} - n_{et-1}$ denote the deviation in employment between year t and $t-1$. Furthermore, let the set of establishments in sector S with $\Delta n_{et} > 0$ be denoted S^+ and let the set of establishments with $\Delta n_{et} < 0$ be denoted S^-.

Gross job creation in sector S in t, C_{st}, is calculated as the sum of all employment deviations in S^+. Correspondingly, gross job destruction, D_{st}, is calculated as the absolute sum of all employment deviations in S^-. To express these measures as rates, the average size of the sector over the year is used as the denominator. Given the nature of data, the best approximation of the plant size during a year is the average of employment in year $t-1$ and t. Accordingly, X_{st} denotes the size of sector S in period t, i.e.

$$X_{st} = \sum_{e \in S} x_{et} \tag{1}$$

where $x_{et} = 0.5(n_{et} + n_{et-1})$.

The job flow rates can be expressed as size-weighted sums over the plants' growth rates, such that the job creation rate and the job destruction rate is given by

$$c_{st} = \frac{C_{st}}{X_{st}} = \sum_{e \in S_t^+} g_{et} \frac{x_{et}}{X_{st}} \tag{2}$$

and

$$d_{st} = \frac{D_{st}}{X_{st}} = \sum_{e \in S_t^-} |g_{et}| \frac{x_{et}}{X_{st}} \tag{3}$$

respectively, where

$$g_{et} = \frac{\Delta n_{et}}{x_{et}} \tag{4}$$

The growth rate (g_{et}) is symmetric around zero and bounded in the $[-2, 2]$ interval, where the upper and lower bound represents the growth rate of an entering plant and an exiting plant, respectively.[8]

The sum of job creation and destruction is job reallocation, R, which measures the total number of employment positions (or jobs) reallocated.

[8] This growth rate used in this study is related to the conventional growth rate, G, (where the value in the base period is used as the denominator) by the following equality: $G = 2g/(2-g)$

The difference between job creation and destruction is the net employment change, NET. That is,

$$r_{st} = \frac{C_{st} + D_{st}}{X_{st}} = \sum_{e \in S_t} |g_{et}| \frac{x_{et}}{X_{st}} \tag{5}$$

and

$$net_{st} = \frac{C_{st} - D_{st}}{X_{st}} = \sum_{e \in S_t} g_{et} \frac{x_{et}}{X_{st}} \tag{6}$$

The number of jobs reallocated does not serve as a good measure of heterogeneity at the micro level, since the job reallocation rate is increasing in absolute employment changes. As a measure of overall heterogeneity in the plant-level employment outcomes, excess job reallocation, ER, is used to denote job reallocation over and above what is needed to accommodate the aggregate net change in employment.

$$er_{st} = r_{st} - abs(net_{st}) \tag{7}$$

Excess job reallocation is bounded in the $[0, r]$ interval, where the lower bound is reached if all establishments change the employment in the same direction; i.e. total job reallocation equals the job reallocation necessary to accommodate the net employment change in the economy.

Job reallocation represents an upper bound for the number of workers who in direct response to job flows have to change jobs or switch between employment and non-employment. It is an upper bound because some workers may be counted twice, as they move from a shrinking to a growing establishment within the period. The minimum number of workers who have to change jobs or switch between employment and non-employment in direct response to job reallocation equals the maximum of job creation and destruction. Thus, the worker reallocation induced by job reallocation, iwr, is bounded by the following interval:

$$iwr_{st} \in [\max(c_{st}, d_{st}), r_{st}] \tag{8}$$

Before the basic job flow statistics are presented, a few caveats about what is measured and not are in place. First, employment changes are interpreted as changes in the desired number of employment positions or jobs. Yet, it is quite possible that some of the observed changes in employment are in fact due to temporary changes in the number of unfilled positions.

(By studying the persistence of job flows, we will get a sense of how important this problem is.) Second, the measures do not discriminate between differences in contracts, e.g. a full-time job and a part-time job do equally count as one.[9]

Estimated job flows are for two reasons also minimum estimates of true job flows. First, a job is simply defined as a filled employment position and, thus, no distinction is made between different kinds of positions, e.g. with respect to the requirements. Substitution between different kinds of jobs within the establishment will, therefore, not fully be accounted for in the job reallocation measure. Second, the timing of data collection makes it impossible to measure job flows that are reversed within a year.

4 Job Flows in Swedish Manufacturing

Using the analytical tools developed in the preceding section, basic facts about the job reallocation process in Swedish Manufacturing, in terms of magnitudes and cyclical behavior will be laid out in this section.

As dramatic as the net employment record shown in Figure 1 is, it only captures the dynamics of the labor market in a very limited sense. The observed net changes in employment have been the sum of large gross flows of jobs at the plant level. During the average year, more than 90,000 jobs are created and destroyed; a number that by large exceeds the net change in employment in any year. Neither the number of new jobs nor the number of lost jobs has fallen short of 20,000 in any year during the period.

Table 1 summarizes the annual job flow statistics for the Swedish Manufacturing sector. A number of interesting facts emerge: 1) There have been non-negligible job flows during every year; but 2) as compared to results on U.S. Manufacturing, the average pace of job reallocation has been slower. 3) There has been a substantial variation over time in the gross job flows; and, in particular, 4) job reallocation exhibits a counter-cyclical pattern.

The average job reallocation rate of 11.8 percent tells us that during the course of the typical year a little more than one in every ten jobs are either created or destroyed. This is the sum of 5.1 percent of the jobs being created and 6.8 percent of the jobs being destroyed; the larger job destruction has resulted in the negative growth rate in net employment of 1.7 percent annually.

[9] See Arai and Heyman (2000) for a job flow study using Swedish data that distinguishes between temporary and permanent contracts.

Table 1: Annual gross job flows in Swedish Manufacturing, 1972-96

Variable	Mean	Std. Dev.	Min	Max	U.S.
Job creation (c_t)	5.1	1.6	2.7	9.3	9.1
Job destruction (d_t)	6.8	3.1	3.9	15.8	10.3
Job reallocation (r_t)	11.8	3.3	8.9	20.4	19.4
Net job creation (net_t)	-1.7	3.8	-11.2	5.0	-1.1
Excess job reallocation (er_t)	9.0	2.1	5.3	14.9	15.4
Min. induced worker reallocation ($iwr_t^{\min}$)	7.3	2.9	4.6	15.8	11.7
Pearson correlations (marginal significance level)					
$\rho(c_t, d_t) = -0.17(0.42)$ $\rho(net_t, r_t) = -0.60(0.00)$					

The last column refers to the U.S. Manufacturing over the 1972-1988 period, as reported by Davis, Haltiwanger and Schuh (1996) Table 2:1, page 19.

The heterogeneity in the plant-level employment outcome is verified by the average excess job reallocation rate of 9.0 percent. Thus, most of the observed job reallocation, has been over and above what is necessary to accommodate the net employment changes in the Manufacturing sector. For instance: During 1995, when employment expanded by 5 percent, gross job destruction was still 4.3 percent. During 1992, when employment shrank by 11.2 percent, gross job creation was still 4.6 percent.

The reported correlation between the net employment change and job reallocation, shows that job reallocation has been significantly counter-cyclical over the period, which is the result of a higher variability in job destruction than in job creation. That the heterogeneity of the plant-level employment outcome increases in times of contraction is a result that has been found also in U.S. Manufacturing (Davis and Haltiwanger, 1992), although the generality of this result has been questioned by other studies (Boeri, 1996). The countercyclical movement in job flows is not in accordance with the idea that the extensive employment protection in Sweden will result in a higher relative variability in job creation as compared to the variability in job destruction (Garibaldi, 1998; Boeri, 1996).

The fifth column reports job flow statistics in U.S. Manufacturing sector over the 1972-88 period, as reported by Davis, Haltiwanger, and Schuh (1996). The differences in the job reallocation numbers between Swedish and American Manufacturing can roughly be summarized by that *for every job reallocated in the Swedish Manufacturing sector, nearly two jobs are reallocated in the U.S. Manufacturing sector, and the heterogeneity, as measured by excess job reallocation, is about 1.5 times larger in the U.S.*

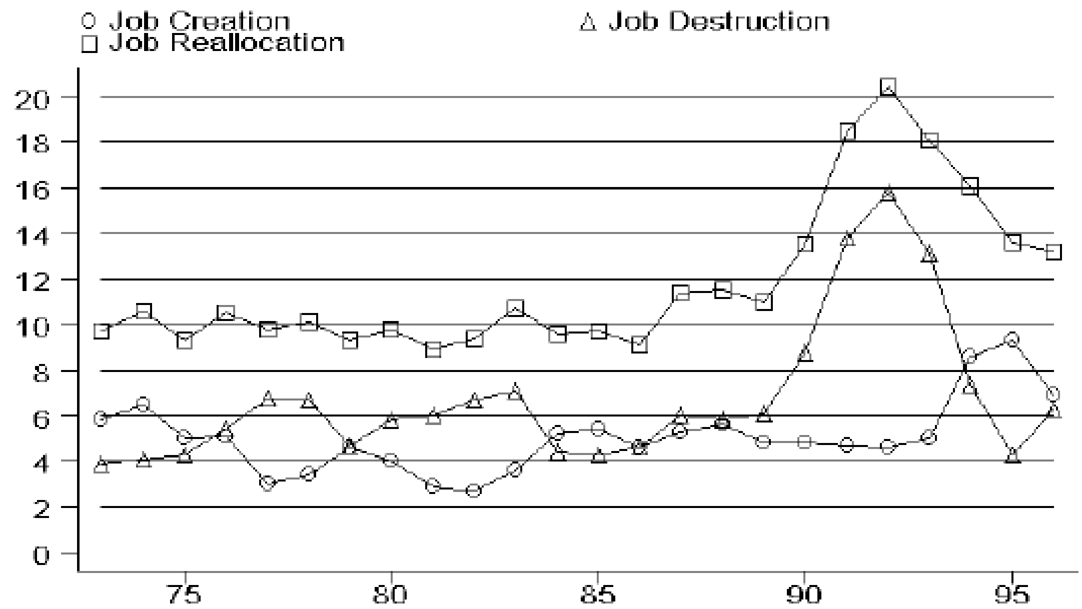

Figure 2: Annual job reallocation rates (in percent) in Swedish Manufacturing, 1972-96

The perception of job flows being relatively modest in Swedish Manufacturing is partly due to the inability of the averages in Table 1 to reveal a changing world. A striking aspect of the job flow statistics is an apparent shift in the job reallocation process, initiated in the late 1980's. In Figure 2 the evolution of job creation, job destruction and job reallocation is shown on a year-by-year basis.

Having oscillated in the 9-11 percent neighborhood in the preceding period, the job reallocation rate started to increase around 1987 to peak in 1992 at a 20.4 percent level: during 1992 more than one in every five jobs were either created or destroyed. The increase in the job reallocation rate reveals that the dramatic fall in Manufacturing employment in the early 1990's was mainly accommodated by an increase in the number of jobs destroyed, rather than by a decrease in the number of jobs created. In fact, there was no marked decrease in job creation at all, and the job creation rate has never been as high as when employment started to recover somewhat during the last three years.

The low average pace of job reallocation in Swedish Manufacturing is consistent with presumably higher adjustment costs in Sweden as compared to the U.S. However, it is hard to interpret the increase in job flows during the last decade in terms of any changes in the institutional settings. Notably, a reduced wage compression, as a result of the abandonment of the "Swedish model" would according to the theoretical model of Bertola and Rogerson (1997) result in lower rates of job reallocation, *ceteris paribus*. Clearly, any such effects are not detectable in the job reallocation pattern in Figure 2.

Potential explanations for the heterogeneity in the plant-level employment outcome and the variation in job flows over time will be addressed in Section 6.

5 The Importance of Job Flows

This section highlights the importance of the job reallocation process, by first emphasizing their consequences on the workforce and then their relationships to economic growth.

5.1 The Relationship Between Job Flows and Worker Mobility

The Connection to Total Worker Reallocation

According to Table 1, job flows have, on average, directly induced worker reallocation in the range of 7.3 to 11.8 percent. It is important to recognize that this range only measures the worker reallocation necessary in direct response to job flows. Secondary waves of worker reallocation in response to job flows are not accounted for, but is the likely result as vacancies are opened when a worker leaves his current position for a newly created job.

Total worker reallocation is induced by establishment heterogeneity, i.e. job flows; by match heterogeneity in excess of establishment heterogeneity, often referred to as churning flows; and by life-cycle motives, e.g. inflow into the labor force from the educational system and outflow from the labor force because of retirements (Burgess, Lane, and Stevens, 2000). If the latter two components are large relative to the former, it is likely that a large fraction of the observed job flows can be accommodated by worker mobility that would have taken place anyway.

In order to evaluate the importance of job flows in explaining worker flows, Table 2 compares the worker reallocation induced by job flows with the total numbers of number of accessions and separations. IS does not contain information on individuals, therefore the total number of persons who switch jobs or employment status has been calculated using data from

Table 2: Worker and job reallocation by year

Year	wr	r	$iwr^{\min}/w_r$	$iwr^{\max}/w_r$
1986	40.5	9.1	0.11	0.22
1987	41.0	11.4	0.15	0.28
1988	42.9	11.5	0.14	0.27
1989	42.9	11.0	0.14	0.26
1990	46.6	13.5	0.19	0.29
1991	34.2	18.5	0.40	0.54
1992	34.6	20.4	0.46	0.59
1993	32.9	18.1	0.40	0.55
1994	31.8	16.1	0.27	0.51
1995	30.2	13.6	0.31	0.45
1996	26.5	13.2	0.26	0.50
Mean	36.7	14.2	0.26	0.41
Pearson Ccrrelation (marginal significance level)				
$\rho((iwr/w_r), net_t) = -0.56(0.07)$				

The fourth and fifth column report the estimated minimum and maximum fraction of total worker reallocation necessary to accomodate worker reallocation. The reported correlation is between the average of minimum and maximum induced worker reallocation as a fraction of total worker reallocation and the net employment change.

the Regional Statistics on Employment (*Årsys*) over the 1985-96 period.[10] A worker who appears among the employees of a particular establishment in year t but not in $t-1$ defines an accession. Similarly, a worker who appears among the employees of a particular establishments in $t-1$ but not in t defines a separation. Total worker reallocation is defined by the sum off all accessions and separations, and is expressed as a rate by dividing with the average employment in the two periods.

According to the calculations presented in Table 2, 36.7 percent of the Manufacturing workforce has changed employment positions or changed be-

[10] Årsys is not available prior to 1985. There are linkage possibilites between IS and Årsys at the establishment level. However, these have not been explored in this paper, mainly because of quality issues regarding the longitudinal links in Årsys. For the same reason the reported worker reallocation rates are somewhat biased upwards and should be interpreted as upper bounds.

tween job and joblessness during the average twelve-month interval in the 1985-96 period. Comparing this figure to the number of individuals who in direct response to job flows have to change between jobs or between jobs and joblessness, we find that between 26 and 41 percent of the observed worker reallocation has been necessary to account for establishment heterogeneity. This fraction has increased over time, as a consequence of both larger flows of jobs and less worker reallocation.

Although total worker reallocation is bounded to be at least as large as worker reallocation induced by job flows, there is a negative correlation between job and worker reallocation. The implied countercyclical movement in the fraction of worker reallocation directly induced by worker flows could be interpreted in terms of workers being more inclined to participate in "job shopping" during economic upturns.

These results indicate that much of the observed worker reallocation is the result of demand factors rather than anything else; in the sense of being induced by shifts in the employment distribution across plants. It also seems like that job flows become increasingly important in recessions in explaining observed patterns of worker mobility.

Concentration

The preceding results established that a large fraction of the observed worker mobility coincides with to shifts in the distribution of employment positions across plants. However, the implication of this result is very different if observed job flows are the result of many plants changing the employment relatively little or if job flows are the resulting sum of relatively few plants changing employment a lot. If the former situation is true, normal worker attrition can probably accommodate most job flows. If the latter instead is true, it can be expected that job destruction is more closely related to the inflow into unemployment and to the outflow from the labor force; and job creation to various bottleneck problems.

Figure 3 shows the distribution of all annual plant-level growth rates over the 1973-96 period. The first thing we learn from the distributions is that the typical situation is that there is no change at all in plant employment. The distribution of growth rates is highly concentrated around zero growth with small endpoint spikes corresponding to births and deaths. On an unweighted basis, 40 percent of the annual growth rates are concentrated in the $(-0.05, 0.05)$ interval and 71 percent in the $(-0.15, 0.15)$ interval. In fact, 25 percent of the observations had a growth rate of exactly zero. We also note that the role for a changing pool of establishments is limited,

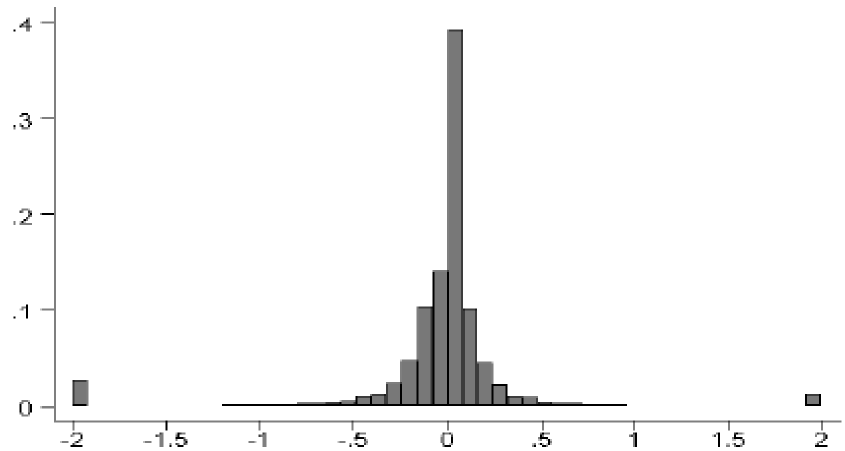

Figure 3: Distribution of annual establiment-level employment growth rates, 1972-96

as very little mass is concentrated at the endpoints.[11] In comparison, the employment-weighted distribution has even less mass concentrated in the tails, suggesting that both establishment turnover and employment volatility are decreasing functions of size. On an employment-weighted basis, 46 and 82 percent are concentrated in the $(-0.05, 0.05)$ and in the $(-0.15, 0.15)$ interval, respectively.

Table 3 instead summarizes the average annual distributions of job creation and destruction by growth rate intervals. A substantial part of job creation and destruction is the result of rather large annual changes in plant-level employment. Around 60 percent of all job destruction during the period has taken place in plants shrinking by more than 20 percent during the course of a year and some 50 percent of job creation has taken place in plants growing with more than 20 percent during the course of a year.[12] In particular, the contribution from entry and exit over the 1972-96 period

[11] In comparison to the growth distribution in U.S. Manufacturing, the distribution of growth rates in Swedish Manufacturing is more concentrated around zero. In particular, less mass is concentrated at the end points. The fact that I have access to adminstrative data on year of entry and exit, which I use to adjust job flow estimates for spurious flows as the result of incomplete data, contributes to explain the difference, but even without any adjustments the results do not change very much.

[12] In comparison, Davis, Haltiwanger, and Schuh (1996) reports that 75 percent of job destruction and 70 percent of job creation are concentrated to plants with an absolute growth reate larger than 0.2.

Table 3: Percentage of annual job creation and destruction accounted for by plants with employment growth rates in the indicated intervals

	Job destruction			Job creation		
Period	$[-2, 1)$	$[-1, -0.2)$	$[-0.2, 0)$	$(0, 0.2]$	$(0.2, 1]$	$(1, 2]$
All years	24.7	35.4	39.9	48.3	31.9	19.8
1972-88	19.7	34.7	45.6	56.7	27.3	16.0
1988-96	31.8	36.5	31.6	33.5	40.1	26.4

was on average 16 percent of job creation and 14 percent of job destruction.

Table 3 also divides the data into the two sub-samples corresponding to the 1972-88 period and to the 1988-96 period. Not only did the magnitude of job reallocation increase; job reallocation also became much more concentrated to plants with larger employment adjustments in the latter period. Whereas almost 70 percent of the mass in the distribution of job reallocation was concentrated to the (-0.5,0.5) interval in the former period, almost 70 percent of all job reallocation took place in plants growing or shirking by more than 20 percent in the latter period.

The results in Figure 3 and Table 3 show that employment changes at the micro level are quite infrequent, but lumpy when they occur. This suggests that normal worker attrition can only account for a limited fraction of the observed job flows.

Persistence

Job reallocation may not be a very persistent phenomenon as a consequence of job flows merely representing changes in the stock of unfilled vacancies, rather than changes in the stock of employment positions, and/or as a consequence of the use of temporary recall and layoff policies.

Table 4, however, shows that job flows, and in particular job destruction, are persistent phenomena: 86 percent of the newly destroyed jobs are still not reopened within a year and 74 percent of the newly created jobs are not destroyed within a year. This suggests that most job flows cannot be implemented by temporary layoff and recall policies.

These figures are somewhat higher than the corresponding figures for the U.S. The difference could possibly be interpreted in terms of higher adjustment costs in the Swedish economy and in terms of temporary contracts being a more important phenomenon in the U.S.

To summarize the likely consequences on the workforce of the job reallocation process, the results show that a large fraction of the observed worker

Table 4: Job flow persistence rates

N-year persistence rate in:	Horizon in years 1	2	3	4	5
Job creation, λ_c^{t+N}	0.74	0.61	0.53	0.46	0.41
Job destruction, λ_d^{t+N}	0.86	0.80	0.76	0.73	0.71
Pearson correlations (marginal significance level)					
$\rho(\lambda_c^1, net_t) = 0.67(0.00)$ $\rho(\lambda_d^1, net_t) = -0.57(0.00)$					

The N-year persistence rate is defined as the fraction of newly created (destroyed) jobs in period t that are not destroyed (created) in any of the consecutive years until t+N.

reallocation is demand driven, in the sense of being induced by shifts in the employment distribution across plants rather than anything else. This finding together with the facts that job flows cannot be implemented by either normal worker attrition or by temporary layoff and recall policies suggest that the job reallocation process has very real consequences for the workforce affected.

5.2 The Importance of Job Flows in the Process of Economic Growth

The creation and destruction of jobs do not only impose mobility requirements on the workforce, but it also benefits the workforce in terms of the productivity effects as the result of job reallocation from less to more productive employers. The importance of job reallocation in the process of growth is hardly a new idea, but has been around since the days of Schumpeter. The notion of *Creative Destruction* involves the necessity to replace old technologies in order to adopt new ones. Modern vintage capital models emphasize the role of entry and exit (Caballero and Hammour, 1995) and retooling (Cooper, Haltiwanger, and Power, 1999) as important mechanisms by which this process is taking place.

Following the methodology of Baily, Hulten, and Campell (1992) and Foster, Haltiwanger, and Krizan (2001), the importance of reallocation of inputs and outputs in explaining the long-run growth in productivity is assessed using the following decomposition methodology: The measure of aggregate productivity used is given by

$$P_t = \sum s_{et} p_{et} \tag{9}$$

where p_{et} is the producer-price deflated, average labor productivity in the e:th unit in period t and s_{et} is its share of total employment. The change in aggregate productivity between period $t-1$ and period t can be decomposed in the following way:

$$\begin{aligned}\Delta P_t &= \sum_{e\in c} s_{et-1}\Delta p_{et} + \sum_{e\in c}\left(p_{et-1} - P_{t-1}\right)\Delta s_{et} + \sum_{e\in c}\Delta p_{et}\Delta s_{et} + \\ &\quad \sum_{e\in n}\left(p_{et} - P_{t-1}\right)s_{et} + \sum_{e\in x}\left(p_{et-1} - P_{t-1}\right)s_{et-1} \qquad (10)\end{aligned}$$

where c denotes the set of continuing plants, n entering plants and x exiting plants. The first term (the within share), measures how much of the growth in productivity that would have taken place without any changes in the distribution of employment shares across the units. The second term (the between share) measures how much of the productivity growth that is due to shifts in the distribution of employment shares across the units, given their initial productivity relative to the aggregate. The third term (the cross term) is a covariance term, which can be interpreted as the fraction of productivity growth that cannot unambiguously be assigned to either of the former sources. The last two terms measure the contribution from entering and exiting plants, respectively (the entry and exit share). If entering plants have higher than average productivity in the base period, they will contribute positively. Similarly, if exiting plants have lower than average productivity in the base period, they will contribute positively to the growth in average productivity.

Table 5 presents the results of such decompositions. The following results emerge: Over the 1972-96 period, 40.7 percent of the productivity growth would have occurred even if the shares of employment among the continuing plants would have had remained unchanged. The flip side of this is that some 60 percent of the growth in productivity over the period can be attributed to various activities that include reallocation of employment shares. The small between share tells us that the role for reallocation of employment shares from low to high productive plants has been quite small. Another 21.2 percent of the growth in productivity is due to the fact that productivity changes and employment shares moved in the same direction; plants experiencing growth in productivity also tended to increase their shares of employment and vice versa. The contribution from entering plants is substantial, which is not so surprising given the long time span.

Several interesting results emerge when the decomposition is carried out for different periods. The three sub-periods correspond to 1972-80, a period

Table 5: Productivity growth decomposition)

Period	Annualized growth	Within share	Between share	Cross share	Entry share	Exit share
1972-96	3.2	40.7	4.9	21.2	30.3	2.8
1972-80	0.7	70.3	53.6	-39.0	-14.0	29.1
1980-88	3.7	84.0	15.1	-8.7	5.5	4.1
1988-96	5.1	57.6	14.3	17.2	8.8	2.1

characterized by a low annualized growth rate in productivity; 1980-88, a period with medium-high growth rate; and 1988-96, a period when the pace of productivity growth was fast. Over the 1972-80 period, the low rate of growth in productivity was achieved in a way that could be characterized as a labor saving. The large contributions from both the within and the between term is counteracted by a large cross term, which implies that most plants that experienced productivity increases also experienced decreases in their employment shares. This is also true, but to a lower extent, for the 1980-88 period. Within-plant changes were the dominating source of the, somewhat higher, growth in productivity.

Already the fact that the 1988-96 period is characterized by a very fast pace of productivity growth is interesting. The change in the way productivity growth came about in this period is also striking. In contrast to the earlier periods, within-plant changes were a less predominant source of productivity growth. The positive and large cross term, shows that most plants that experienced productivity growth also increased their employment shares.

In accordance with the view that entry and exit are important features in the process of growth, we find that the overall contribution from plant turnover has been positive in each of the period considered. In the 1972-80 period this is true as a consequence of a substantial contribution from exiting plants (at least in relative terms). Entering plants, on the other had, did in fact contribute negatively. In the 1989-96 period, we note that the role for entry is quite important; together with exiting plants, entering plants accounted for some 10 percent of the high growth in productivity.

The conclusion is that the reallocation of inputs across plants plays an important role in accounting for the growth in aggregate productivity. Furthermore, the relative importance of each component varies substantially over time. With respect to the 1988-96 period, as compared to the previous periods it is particularly interesting that we find that a large fraction of the fast pace of growth in productivity can be attributed to reallocation activities and that the growth came about in a quite different way. These are interesting facts as they suggest that the increases in the job reallocation rates in the 1990s are closely associated with the way growth came about.

6 Explanations for Simultaneous Job Creation and Destruction

The preceding sections presented basic facts about the job reallocation process in Swedish Manufacturing. Two major findings stand out: First, during every year, large gross flows of jobs, over and above what is needed to accommodate the net change in employment, can be observed. Second the job reallocation rate varies considerably over time. Motivated by the consequences on the workforce and the relationship to economic growth, this section systematically investigates the sources of the heterogeneity in plant-level employment outcomes. In particular, 1) what explains simultaneous job creation and destruction, and 2) why does the rate of job reallocation vary over time?

Reasons for why jobs are created and destroyed simultaneously are clearly not to be found in the traditional framework of representative agents. However, the notion of heterogeneity is admittedly dependent on the level of abstraction. Thus, an immediate objection against interpreting simultaneous job creation and job destruction as heterogeneity is the possibility that the seemingly heterogeneous behavior is caused by asymmetries across sectors. That is, the high rates of excess job reallocation could be the result of that jobs are created in certain sectors of the economy while destroyed in others.

Differences in the employment outcome across industries might arise for a number of reasons, including differences in the product demand conditions and the utilization of different mixes of inputs. Regional differences, apart from reflecting different industrial mixes, could arise as a consequence of regional differences in the cost of labor, transportation, energy etc.

Also for within-sector heterogeneity there are theoretical explanations. In the literature that involves selection effects (Jovanovic, 1982; Ericson and a Pakes, 1995; Hopenhayn, 1992) plants face *ex ante* uncertainty about their true efficiency. Plants that accumulate favorable information about their efficiency expand and survive, whereas the less favored plants exit the market. Given that age and size can serve as proxies for the plants' stage in the process of initial learning, this literature implies that job flows would be a decreasing function of these characteristics.

Although the human capital literature, by itself, cannot explain the simultaneous occurrence of job creation and destruction, it adds to our understanding, in the sense that it has implications for the magnitudes of job flows. As pointed out already by Oi (1962), a high degree of firm-specific capital would result in a more permanent relationship between the individual and the plant. The wage is likely to be correlated with the amount of firm-specific capital in labor and, thus, job creation and destruction are expected to be decreasing in wages.

The vintage capital literature provides another rationale for why jobs are created and destroyed simultaneously. Sunk costs associated with the installation of new capital in association with technological progress or idiosyncratic chocks give rise to job flows in excess of the net employment change. In the model of Caballero and Hammour (1995) new technology can only be adopted by the entry of new establishments and, thus, the only sources of job reallocation is through entry and exit. Instead, in the model of Cooper, Haltiwanger, and Power (1999) existing plants adopt new technology by retooling. The retooling process may generate within-plant and between-plant job reallocation depending on the nature of the new technology.

These models also have implications for the timing of the reallocation process. Aggregate disturbances, in product demand for instance, will in such models generally give rise to a countercyclical movement in job flows. Differences in the level of productivity across the plants imply that plants will react quite differently to an adverse shock. Possibly a large fraction of the low-productive plants will be pushed over an adjustment threshold, and as a consequence they are forced to react by either updating their technology or exit. Thus, such a process could account for our finding that job reallocation seems to be countercyclical. A competing explanation is that there are systematic differences across sectors in the responses to aggregate disturbances, which is an important element in the traditional view of the business cycle (Abraham and Katz, 1986).

6.1 Why are Jobs Created and Destroyed Simultaneously?

It is beyond the scope of this paper to evaluate each of these theoretical strands of literature, but the preceding remarks at least identify some of the factors that could affect job flow patterns. Table 6-9 present job flows by industries, location and other plant characteristics. When dividing the Manufacturing into industries (Table 6) and into regions (Table 7), the results show that the job flow pattern in each and every industry and region,

Table 6: Job flows by industry (annual averages)

Industry	c_{st}	d_{st}	net_{st}	r_{st}	$iwr_{st}^{\max}$	er_{st}	X_{st}/X_t
Mining	4.5	7.5	-3.0	12.0	8.7	6.5	1.4
Food	4.8	5.9	-1.1	10.6	6.2	8.8	8.4
Textile	4.3	9.6	-5.4	13.9	9.7	8.4	5.0
Wood etc.	5.0	7.3	-2.4	12.3	7.9	8.8	7.7
Paper	3.1	4.3	-1.3	7.4	4.8	5.3	6.8
Printing	4.4	5.8	-1.4	10.3	6.2	8.2	5.1
Chemicals	5.1	5.8	-0.7	10.9	6.9	8.1	5.3
Rubber	4.6	7.8	-3.2	12.4	8.3	8.1	1.2
Plastics	6.4	6.6	-0.2	13.0	8.6	8.8	1.5
Stone, Clay & Glass	4.7	7.9	-3.2	12.6	8.2	8.7	3.1
Primary Metals	3.5	5.9	-2.3	9.4	6.4	5.9	6.7
Fabricated Metals	6.0	7.4	-1.4	13.4	8.4	10.0	8.8
Non-electric Machinery	4.9	6.9	-2.0	11.8	7.6	8.4	13.4
Electric Machinery	7.1	6.4	0.8	13.5	8.5	10.0	8.7
Transportation	4.8	4.8	0.0	9.6	6.8	5.6	11.2
Instruments	7.5	7.1	0.3	14.6	9.8	9.6	1.7
Shipyard	4.0	9.9	-6.0	13.9	11.2	5.4	3.2
Miscellaneous	5.0	7.9	-2.9	12.8	8.4	8.8	0.7
Size-weighted, cross-industry std. dev.	1.1	1.4	1.6	1.9	1.4	1.6	

Size-weighted, cross-industry correlations (marginal significance level)

$\rho(c_{st}, d_{st}) = 0.18(0.50)$ $\rho(net_{st}, r_{st}) = -0.26(0.31)$

with few exceptions, resembles the aggregate picture presented in Table 1.[13] Average, annual job reallocation rates range between 7.4 and 14.6 percent in the industries and between 9.7 and 13.8 percent in the regions. If job creation and job destruction mainly would be the resulting sum of asymmetries across sectors, we would expect the within-sector excess job reallocation to be a less predominant feature. Clearly, the average job reallocation rates in the different industries and regions are not the resulting sums of jobs being created in certain periods and jobs destroyed in other periods, which is verified by high excess job reallocation rates. Thus, the observed heterogeneous employment outcome across plants is not mainly an artifact of industry or regional effects.

In Table 8 net and gross job flows are tabulated by size and age of firms

[13] I thank Erika Ekström, Gudmundur Gunnarsson and Erik Mellander for providing me with cross-walks between new (SNI92) and old (SNI69) SIC codes.

Table 7: Job flows by region (annual averages)

Region ("Län")	c_{st}	d_{st}	net_{st}	r_{st}	$iwr_{st}^{\min}$	er_{st}	X_{st}/X_t
Stockholm	6.4	7.4	-1.0	13.8	8.3	11.0	11.7
Uppsala	4.9	7.3	-2.4	12.2	7.9	8.5	1.9
Södermaland	4.3	6.7	-2.4	11.0	7.2	7.5	3.7
Östergötland	4.8	6.4	-1.5	11.2	7.0	8.4	5.8
Jönköpning	4.9	6.1	-1.2	11.1	7.1	7.9	5.3
Kronoberg	5.2	5.9	-0.7	11.1	7.1	8.0	2.6
Kalmar	4.8	6.1	-1.3	11.0	7.1	7.7	3.7
Gotland	5.3	5.9	-0.6	11.1	7.9	6.5	0.4
Blekinge	4.3	5.8	-1.5	10.1	6.7	6.8	2.5
Kristianstad	5.4	6.8	-1.4	12.2	7.9	8.7	3.5
Malmöhus	4.8	6.9	-2.1	11.7	7.1	9.2	8.4
Halland	4.9	6.3	-1.4	11.1	7.0	8.3	2.4
Göteborgs och Bohus	5.1	7.1	-2.0	12.1	7.7	8.8	8.7
Älvsborg	4.5	6.2	-1.6	10.7	6.9	7.5	6.7
Skaraborg	4.9	5.3	-0.4	10.3	6.8	6.9	4.0
Värmland	4.4	6.2	-1.8	10.5	6.8	7.4	3.8
Örebro	4.2	6.0	-1.8	10.3	6.7	7.1	4.0
Västmaland	4.5	6.0	-1.5	10.5	7.0	7.1	4.5
Kopparberg	4.3	6.3	-2.0	10.6	7.0	7.2	3.8
Gävleborg	4.1	5.7	-1.6	9.7	6.5	6.4	4.2
Västernorrland	4.7	6.5	-1.8	11.2	7.2	8.2	2.9
Jämtland	6.3	7.5	-1.3	13.8	9.2	9.3	0.8
Västerbotten	5.3	6.2	-0.9	11.5	7.6	7.8	2.4
Norrbotten	5.8	6.4	-0.6	12.2	8.3	7.8	2.4
Size-weighted cross-region std. dev.	0.7	0.6	0.5	1.1	0.6	1.3	

Size-weighted cross-region correlations (marginal significance level)

$\rho(c_{st}, d_{st}) = 0.67(0.00)$ $\rho(net_{st}, r_{st}) = 0.19(0.40)$

Table 8: Job flows by plant size, age and ownership type

	c_{st}	d_{st}	net_{st}	r_{st}	$iwr_{st}^{\min}$	er_{st}	X_{st}/X_t
			Employment size				
$1-10$	7.8	13.6	-5.8	21.4	13.8	15.2	2.0
$11-25$	7.4	9.7	-2.3	17.0	10.2	13.6	7.5
$26-50$	6.8	8.5	-1.6	15.3	9.2	12.1	8.4
$51-100$	5.9	7.6	-1.7	13.5	8.2	10.5	10.7
$101-250$	5.1	6.8	-1.7	11.8	7.3	9.1	18.1
$251-500$	4.7	5.9	-1.3	10.6	6.6	8.0	14.4
$501-1000$	3.9	5.1	-1.1	9.0	5.9	6.3	15.1
>1000	3.6	4.7	-1.1	8.3	5.8	5.1	23.9
			Plant age (in years)				
0	200	0.0	200	200	200	0.0	0.3
0-2	7.9	11.0	-3.1	18.9	11.8	14.1	3.6
3-5	6.6	9.1	-2.4	15.7	10.4	10.7	4.4
5-10	5.8	7.9	-2.1	13.7	8.3	10.8	5.3
10 +	5.7	7.2	-1.5	13.0	8.4	9.1	7.2
n.a.	3.9	6.0	-2.1	9.8	6.3	7.1	79.2
			Ownership type				
Single-unit	5.9	7.5	-1.6	13.5	8.3	10.4	33.0
Multi-unit	4.4	5.9	-1.5	10.4	6.4	7.9	67.0

Employment size refers to current employment size. The n.a. group for age includes plants that entered 1972 or prior. Ownership type refers to whether the plant constitutes a firm (singleunit) or is part of a larger firm (multiunit).

Table 9: Job flows by labor productivity and wage cost categories

	c_{st}	d_{st}	net_{st}	r_{st}	$iwr_{st}^{\min}$	er_{st}	X_{st}/X_t
			Average Labor Productivity by Decile				
1:st	10.1	25.5	-15.4	35.6	25.5	20.2	5.8
2:nd	7.0	8.3	-1.3	15.4	9.5	11.7	5.6
3:d	4.5	6.8	-2.3	11.3	7.5	7.7	7.1
4:th	4.8	6.0	-1.2	10.8	7.1	7.5	8.6
5:th	4.5	5.8	-1.3	10.3	6.7	7.1	9.2
6:th	4.2	5.1	-0.9	9.3	6.0	6.6	10.1
7:th	4.0	4.7	-0.7	8.7	5.4	6.5	11.2
8:th	4.1	5.2	-1.1	9.4	5.9	7.0	12.6
9:th	4.5	4.5	0.0	8.9	5.6	6.7	14.1
10:th	5.1	4.3	0.8	9.3	5.9	6.9	15.6
			Average wage cost by decile				
1:st	22.1	37.0	-14.9	59.0	38.1	41.7	5.8
2:nd	6.4	7.4	-1.0	13.8	8.6	10.5	5.6
3:d	5.6	5.7	-0.1	11.3	7.4	7.8	7.1
4:th	5.0	5.4	-0.4	10.4	6.5	7.8	8.6
5:th	4.8	5.2	-0.4	9.9	6.4	7.0	9.2
6:th	4.3	5.5	-1.1	9.8	6.2	7.2	10.1
7:th	4.1	5.3	-1.2	9.4	6.1	6.7	11.2
8:th	3.8	5.6	-1.8	9.4	6.1	6.6	12.6
9:th	3.8	5.2	-1.4	9.0	5.9	6.3	14.1
10:th	4.1	5.1	-1.0	9.2	5.8	6.7	15.6

Each plant has been categorized with respect to which decile of the average labor productivity and average wage cost distributions it belongs to in each year. Average labor productivity is defined as total sales over employment. Average wage costs is total payroll, including payroll taxes, over employment.

and ownership type. According to the first panel, smaller establishments are more volatile than the larger ones are. Smaller establishments do not only create jobs in disproportional numbers, but they also destroy jobs in disproportional numbers. The smaller establishments have actually contributed more to the negative employment record, than the larger ones have. Given the focus on small plants in the public discussion, it is also worth noting that, although the smaller establishments are more dynamic, a limited share of the work force is employed by them, why most jobs are actually created (and for that matter destroyed) by larger establishments. With respect to another size-measure, whether the plant constitutes the whole firm or a part of a firm (single- or multi-plant), we find that the job reallocation rate is higher in the former type of establishments. According to the results in the second panel, younger plants do not only create, but also destroy more jobs than the older ones do. In fact, there is no clear relationship between the net job creation rate and age.

Table 9 presents job flows by labor productivity and average wage costs of plants. We find that job reallocation does more or less monotonically fall with wage costs and productivity. Low productive- and low wage cost plants tend to both create and destroy in disproportional numbers.

By and large these results conform to the results reported in Davis, Haltiwanger, and Schuh (1996) on U.S. Manufacturing, namely that job reallocation is decreasing in size, age, wages and productivity, and that singleunit plants are more volatile than multiunit plants.

Thus far we have established that there are no single bivariate relationships able to explain why jobs are created and destroyed simultaneously. Still, the hypothesis that the observed heterogeneity is the combined result of various sectoral asymmetries cannot be rejected. Consider how we can assess this hypothesis, by decomposing the excess job reallocation into the contribution from between-sector employment shifts and into the contribution from excess job reallocation (heterogeneity) within the sectors.

Recall that the measure of heterogeneity, the excess job reallocation, is defined as $er_{st} = r_{st} - abs(net_{st})$. Following Davis and Haltiwanger (1992) this measure can be decomposed into what is due to between-sector differences and what is due to within-sector heterogeneity. By recognizing that the aggregate job reallocation rate is the size-weighted sum of the job reallocation rates in each sector and by adding and subtracting the size-weighted absolute sum of the net employment change rates in each sector, the excess job reallocation rate can be expressed as:

$$er_t = \sum_s \left(\frac{X_{st}}{X_t}\right)(r_{st} - abs(net_{st})) + \sum_s \left(\frac{X_{st}}{X_t}\right)(abs(net_{st}) - abs(net_t)) \tag{11}$$

where s indexes measures applying for the sector. The first component measures the contribution of within-sector heterogeneity (excess job reallocation) in the employment outcome and the second component measures the contribution of between-sector employment shifts to the overall excess job reallocation. Thus, if the high level of aggregation causes the heterogeneity in the employment outcome across plants, the first component would approach zero as the economy is divided into sectors.

The results of such decompositions are presented in Table 10. The sample is divided with respect to 18 industries, 24 regions, 3 categories of plant size, wage costs, labor productivity and age, and ownership type. Though cross-sector differences in the employment outcome account for some of the observed heterogeneity in the employment outcome, the inability to explain more is still the key finding from the table. For instance, according to the first column, employment shifts across industries on average account for no more than 8 percent, and in no single year more than 22 percent, of the observed excess job reallocation.[14] Regional differences explain even less of the observed heterogeneity. The simultaneous contribution to the observed heterogeneity of industry-, wage- and productivity effects is on average 27 percent; industry-, size- and age effects account for 21 percent; and industry-, region- and ownership-effects account for 35 percent. When all these factors, but regional effects, are allowed to interact still less than half of the observed heterogeneity in the employment outcome can be explained by cross-sector shifts. This is not a lot considering the large number of sectors relative to about 10,000 plants in each year. Thus, the observed heterogeneity is not an artifact of the high level of aggregation, but, instead, most of the observed job reallocation in Manufacturing takes place within narrowly defined sectors.

An interesting exercise in this context is to investigate whether the changes in wage dispersion associated with the changes in the Swedish wage setting system also have been associated with changes in the nature of heterogeneity in job flows. Remember from the introductory remarks that the

[14] If instead detailed industry, i.e. 4-digit SIC, is used to divide Manufacturing, still only a limited fraction of er can be explained by between-industry shifts. Because of changes in the classification scheme of industries, this can only be done for the period 1972-93 and 1990-96, separately.

Table 10: Decomposition of excess job reallocation

Sector Division by:	Industry	Region	Industry, Size, Age	Industry, Wage, Productivity	Industry, Region, Owner	All
# of Sectors	18	24	162	162	864	2,916
Fraction of excess job reallocation accounted for by:						
Between shifts (a)	0.08	0.05	0.21	0.27	0.35	0.47
Within shifts (b)	0.92	0.95	0.79	0.73	0.65	0.53
Std. dev.	0.08	0.05	0.09	0.11	0.09	0.07
Min (a)	0.00	0.00	0.04	0.08	0.17	0.34
Max (a)	0.22	0.19	0.32	0.45	0.48	0.58

Correlations between cross-industry job reallocation and wage dispersion (sign.)

$\rho(a_t, cvw_t) = -0.23(0.28)$ $\rho(a_t * er_t, cvw_t) = -0.11(0.60)$

The "All" column divides Manufacturing by industry, categories of size, age, wage, productivity and ownership type. Industries, regions and ownership types are defined the same way as in Table 6-8. With respect to size, wage and productivity each plant is classified according to which tertile of the distributions it belongs to in each year. The three age classes are: 0-5, 6-10, or older than 10 years or not accounted for (i.e. born prior to 1970). The reported correlations are between, on the one hand, the fraction and the level of excess job reallocation due to between-industry shifts and, on the other hand, the cross industry wage dispersion, measured as the squared coefficient of variation.

wage dispersion has increased in the Swedish Manufacturing since sometimes around the mid-1980s when centralized negotiations where abandoned in favor of negotiations on the industry level. Although the increasing wage dispersion has been associated with increasing, rather than decreasing, job reallocation, still, one hypothesis is that cross-industry job reallocation became less important, as the wage dispersion between the industries increased. In the lower panel of Table 10 the correlation between the relative, a_t, the absolute, $a_t er_t$, cross-industry job reallocation and the cross-industry wage dispersion is shown, respectively.[15] Consistent with the hypothesis the point estimates are negative. However, the correlations are not significant.

6.2 Why Does Job Reallocation Vary over Time?

The results in the preceding section suggest that plant-level idiosyncrasies are important, in the sense that asymmetries across sectors account for only a small fraction of the heterogeneous employment outcome across plants. It seems natural to assume that variation in such idiosyncrasies is also important in explaining the variation of job flows over time. If so, a well-stated macro economic theory trying to explain the cyclical pattern of jobs should be able to come up with a rationale for why idiosyncrasies in the employment outcome become more important in times of contraction.[16]

However, before such a claim is made, the possibility that the observed countercyclical pattern is an artifact of possible aggregate and sectoral effects should be ruled out. That is, the observed countercyclical pattern could be the result of contractions as times of increased heterogeneity across sectors and not necessarily by increased heterogeneity within the sectors. There is nothing incoherent in recognizing the importance of idiosyncrasies in explaining the cross-sectional variance in job flows, but at the same time argue the importance of aggregate forces in explaining the variation in job flows over time.

To discriminate between the view that the variation in job flows is mainly driven by aggregate forces from the view that idiosyncrasies are important also in this sense, the plant-level growth rate is decomposed into an aggregate, a sectoral, and an idiosyncratic component. Let $\widetilde{g}_{et}$ be the idiosyncratic component in plant-level growth and let $\overline{net}_{st}$ be the deviation in the sector

[15] The between-industry wage disperision is measured as the difference between the total wage disperision across plants and the sum of the size-weighted within-industry.

[16] Theoretical models acknowledging this fact include Blanchard and Diamond (1990), Davis and Haltiwanger (1990), and Caballero and Hammour (1995).

growth grate from the aggregate growth, net_t, i.e.

$$\widetilde{g}_{et} = g_{et} - \overline{net}_{st} - net_t \tag{12}$$

By calculating the idiosyncratic gross flow measures (denoted by tildes) using the idiosyncratic distribution of growth rates, the overall variance in the job reallocation rate can be decomposes as

$$var(r_t) = var(\widetilde{r}_t) + var(r_t - \widetilde{r}_t) + 2cov(\widetilde{r}_t, r_t - \widetilde{r}_t) \tag{13}$$

where

$$\widetilde{r}_t = \sum_{e \in S} \frac{x_{et}}{X_{st}} |\widetilde{g}_{et}|^{17} \tag{14}$$

The identifying assumption is that if the variation over time in the job reallocation rate would be completely driven by aggregate and/or sectoral forces, the distribution of the idiosyncratic growth rates would be time-invariant. In terms of the decomposition, this implies that and that all variance in job reallocation can be accounted for by aggregate and sectoral mean translation effects on the distribution of growth rates, as measured by the second term. The covariance term reflects the part of the variation that cannot unambiguously be assigned to either aggregate or idiosyncratic effects.

Table 11 presents the results from such decompositions under different assumptions about the nature of shocks. In the first column the assumption is that shifts in the aggregate growth, net_t, is the only driving force of the variation in job reallocation; i.e. the distribution of $\widetilde{g}_{et}$ is time-invariant. This view is extended in the following columns to allow also for sectoral deviations with respect to industry, size, ownership type, age, region, wages, productivity and combinations thereof.

The contributions from aggregate and sectoral mean effects account only for a minor fraction of the observed variance in job reallocation; the second term in the variance decomposition accounts for between zero and six percent of the variance in the job reallocation rate. Even if the whole covariance term is assigned to the aggregate and sectoral effects, the contribution is still limited.

[17] Also this decomposition appears in Davis and Haltiwanger (1992). Note that the concept of heterogeneity is extended using the idiosyncratic job reallocation rate in comparison to the excess job reallocation rate. The latter only measures the extent to which jobs are created and destroyed simultaneously, whereas the former in addition takes into account differences in growth rates across sectors.

However, looking at the second and third panel of the table, aggregate shift stories seems to be more important in explaining the variation over time in job destruction and job creation, respectively. What explain the relationships between the behavior of job reallocation and the behavior of job creation and job destruction, are the covariance results. For job destruction, the covariance results indicate that idiosyncratic effects strongly reinforce the countercyclical movements, whereas for job creation, the covariance results indicate that idiosyncratic effects counteract the procyclical movement.

The fourth panel reports the size-weighted average correlation between the idiosyncratic job reallocation rate and the own-sector employment growth rate. We note that the negative countercyclical movements in job flows are

Table 11: Decomposition of time-series variance in job flows

Sectors:	Total Mfg.	Industry	Region	Ind., Size, Age	Ind., Wage, Prod.	Ind., Reg., Owner	All
# of sectors	1	18	24	108	162	864	2,916
Fraction of job reallocation variance accounted for by: (a) sectoral/aggregate mean effects and (b) Idiosyncratic effects							
(a)	0	0.01	0	0.02	0.02	0.03	0.06
(b)	0.93	0.92	0.93	0.91	0.88	0.8	0.62
2cov(a,b)	0.07	0.07	0.07	0.07	0.1	0.18	0.32
Fraction of job creation variance accounted for by: (a) sectoral/aggregate mean effects and (b) idiosyncratic effects:							
(a)	1.36	1.37	1.34	1.38	1.29	1.29	1.13
(b)	0.97	0.96	0.97	0.96	0.91	0.84	0.74
2cov(a,b)	-1.32	-1.33	-1.31	-1.34	-1.2	-1.13	-0.87
Fraction of job destruction variance accounted for by: (a) sectoral/aggregate mean effects and (b) idiosyncratic effects:							
(a)	0.37	0.37	0.38	0.36	0.39	0.39	0.45
(b)	0.25	0.25	0.24	0.25	0.24	0.22	0.19
2cov(a,b)	0.38	0.38	0.37	0.39	0.37	0.39	0.36
Average, size-weighted correlations between net_{st} and $\widetilde{r}_{st}$							
ρ	-0.61	-0.63	-0.60	-0.51	-0.34	-0.30	-0.26
(#<0/total)	1	0.94	0.96	0.89	0.81	0.70	0.56

The "All" column divides Manufacturing by industry, size, age wage, productivity and ownership type. See notes in Table 10 for definitions of the various sectors.

remarkably uniform across the various sectors. For instance, the correlations are negative in all but one industry. Thus, if anything, aggregate and sectoral effects reinforce, rather than explain, the finding that job reallocation is countercyclical. The countercyclical property of job flows is thus not an artifact unique to U.S. Manufacturing, but is also pervasive in Swedish Manufacturing.

While the previous results provide strong evidence in favor of the countercyclical behavior of the heterogeneity in the employment outcome across plants, they say little about the magnitude of the covariances between net overall and sectoral growth rates, on the one hand, and sectoral job reallocation rates, on the other hand. To investigate the covariance structure, Table 12 regresses the rates of idiosyncratic job reallocation on the Manufacturing net employment growth and the own-sector net employment growth deviated about the Manufacturing growth. The regressions also contain sectoral fixed effects to control for permanent sectoral differences in the intensity of job reallocation.

For instance, in regression (1) the idiosyncratic job reallocation rates in the 18 industries are regressed on the time varying covariates and 18 fixed industry effects. The time varying covariates are highly significant and together they account for 50 percent of the variation in industry job reallocation rates. The covariance structure implies that a one standard deviation decline in the Manufacturing (own-industry) growth rate is associated with an increase in sectoral job reallocation rates of 6.04 (3.81) percentage points.

Relative to the time-varying covariates in regression (1), regressions (2)-(4) add interactions of size-, age-, ownership-, productivity- and wage cost dummies. A number of interesting results emerge. First, large movements in the idiosyncratic job reallocation rates are associated primarily with movements in the Manufacturing employment growth rate, rather than with movements in the own-sector employment growth rate. Second, the covariation between the Manufacturing employment growth rate and the idiosyncratic sectoral job reallocation rates is larger among smaller plants than in larger plants, among low productive plants than in high productive plants, and among low wage cost plants than in high wage cost plants.[18] A similar but less pronounced pattern is found with respect to the own-sector growth rate.

[18] That the countercyclical property of job reallocation is more pronounced among smaller plants differ from the results found in U.S. data (Davis and Haltiwanger, 1992). This is an interesting result, since it has been argued that the countercyclical pattern of job flows is an artifact of the size distribution in Manufacturing (Boeri, 1996).

7 Summary

This study documents some of the properties, consequences and reasons for the job reallocation process in Swedish Manufacturing. Based on the argument that the underlying data sources are similar, the results are compared to results based on data for the U.S. Manufacturing, as presented by Davis, Haltiwanger, and Schuh (1996).

The results show that the job reallocation process in Swedish Manufacturing is characterized by large gross flows of jobs, over and above what is needed to accommodate the net change in employment. However, the average pace of job reallocation has been considerably slower than in U.S. Manufacturing. A tentative explanation for the discrepancy between Swedish and U.S. Manufacturing with respect to the average pace of job reallocation could be made in terms of larger adjustment costs in the Swedish economy.

Another key finding is that the intensity of job reallocation has varied considerably over time. Masked behind low averages, there are periods of large-scale job reallocation. In particular, the 1990s are characterized by very high rates of job reallocation, In general, we found that job reallocation exhibits countercyclical movements.

The paper also presents results on some of the economic consequences of the job reallocation process, in terms of its affects on the workforce and economic growth. Several pieces of evidence are presented suggesting that much of the observed worker mobility is the direct result of demand factors, in the sense of being induced by the reshuffling of jobs across work-sites rather than anything else. This claim is based upon two observations. First, we found that, at the very least, some 26-41 percent of the actual worker reallocation in the typical year during the 1985-96 period was directly induced by shifts in the distribution of employment positions across plants. Second, job flows are highly concentrated to plants experiencing large changes in employment, rather than being distributed more evenly across establishments; some 60 percent of job destruction and some 50 percent of job creation took place in plants shrinking and growing by more than 20 percent during the course of a year, respectively. Together these findings suggests that normal worker attrition can be expected to accommodate only a minor fraction of the observed job flows. In addition, job flows are highly persistent phenomena, which implies that job flows cannot be implemented by temporary layoff and recall policies.

Another consequence of the job reallocation process is that it contributes to the process of economic growth. The study investigates the importance of the reallocation of inputs and outputs in accounting for the long-run growth in productivity. The results show that the reallocation of labor from less to more productive establishments have contributed substantially to the growth in productivity. For instance, over the 1972-96 period some 60 percent of the growth in productivity could be attributed to activities that include the reallocation of inputs across plants. Furthermore, we found that the way growth came about varied a lot in different periods. Because of the apparently different job reallocation pattern in this period, it was particularly interesting that we found an increased and, as compared to the other periods, a different role of the various reallocation activities in accounting for the rapid growth in productivity in the 1988-96 period.

Motivated by the consequences for the workforce and the relationships to economic growth, the paper finally investigated into the driving forces of why jobs are created and destroyed simultaneously and what causes the pace of job reallocation to vary over time. The hypothesis that the heterogeneity is the resulting sum of cross-sectional variation in the employment outcome is strongly rejected. Instead, the heterogeneity of the plant-level employment outcome is a pervasive phenomenon even within narrowly defined sectors of the Manufacturing sector. Aggregate and sectoral shift stories do not have any greater success in explaining why the job reallocation varies over time. Instead, a strong finding is that the plant-level idiosyncrasies dominate the variation in job reallocation. The countercyclical behavior of job reallocation was found to be pervasive across sectors, but this pattern seems to be especially pronounced in smaller, low-productive, low-wage cost plants.

Most of these findings are in accordance with models that acknowledge growth and adoption of new technology as a noisy process, filled with experimentation and uncertain outcomes.

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Essay II

Determinants of Plant Closures in Swedish Manufacturing

Determinants of Plant Closures in Swedish Manufacturing*

1 Introduction

This study sheds new light on possible sources of producer heterogeneity, within and across industries, by studying the determinants of plant failure in Swedish Manufacturing during the 1990-96 period using longitudinal matched employee-employer data.

The creation and destruction of production units play an integral part in the growth process and have important implications for the individuals in the work force. For instance: In Swedish Manufacturing at least some 10 percent of the growth in productivity over the 1989-1996 period can be directly attributed to the fact that entering plants had higher than average productivity and that exiting plants had lower than average productivity. Measured in terms of annual job reallocation, plant turnover constitutes some 15-30 percent of all jobs reallocated in Swedish Manufacturing and becomes increasingly important in the longer run (Andersson, 1999). In spite of their important consequences, the existing knowledge about the driving forces of plant closures is quite scarce.[1]

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We derive hypotheses about the determinants of plant exit from a model of imperfect competition in which plants are exposed to stochastic productivity shocks that are realized after wages have been determined in plant-level negotiations. This way there are direct links between the likelihood of plant failure and industry-specific characteristics of production and product demand, on the one hand, and between the likelihood of plant failure and the local labor market conditions, on the other hand. If it further is assumed that only 'insiders' (workers with some seniority) are party of the negotiations (Lindbeck and Snower, 1989), insider mechanisms are introduced as a possible explanation for within-industry differences in the failure probability across plants. In particular, we expect higher wage pressure and higher risks of plant closures in plants with relatively few insiders, since the *ex ante* risk of dismissal for an insider is lower as compared to the risk of dismissal for an insider in a plant with many insiders. Access to longitudinal linked employer-employee data enables us to separate insiders from outsiders in terms of their plant-level seniority.

Another virtue of using linked employer-employee data is that we are able to analyze possible effects of the plant's human capital structure on the exit probability. Investments in plant-specific human capital through training or learning-by-doing would generally increase the rents to be shared between the worker and the firm. Given that the extra rents generated are not fully captured by the workers, this would provide a rationale for why plants with workers having a high degree of plant-specific human capital exhibit a higher reluctancy to shut down operations. Another reason why the human capital structure of a plant could make a difference for the shut-down decision is if there are non-uniform costs associated with the dismissal of workers.

Another possible source of heterogeneity that we consider are plant-specific age effects. Models that emphasize selection mechanism (e.g. Jovanovic, 1982; Pakes and Ericson, 1992) predict that younger establishments are more likely to exit than older ones are because of greater uncertainty surrounding their true efficiency level. The empirical support is strong for high exit rates among young plants (Audretsch and Mahmood, 1994; Audretsch and Mahmood, 1995; Persson, 1999; Sanghamitra and Krishna, 1997; Boeri and Bellman, 1995; Mata and Portugal, 1994).

A partly competing hypothesis could be derived from the capital vintage literature (e.g. Solow, 1956). Interpreted at the micro level, this literature

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1995) is dedicated to plant turnover and growth pattern of firms and plants. Also in the job flow literature, many contributions to our understanding of the post-entry behavior of plants can be found (e.g. Davis, Haltiwanger, and Schuh, 1996).

suggests that establishments using technologies of older vintages are more likely to exit, as they utilize less efficient technologies. Technology vintage effects have received little empirical attentition and, if at all discussed, been rejected as important based on the finding that the hazard of plant failure is decreasing in plant age. This conclusion might be premature, since plant and technology age do not need to coincide, as is the case in some more recent capital vintage models that stress the possibility of updating to newer technology without shutting down the establishment. If this is the case a negative duration dependence with respect to plant age cannot be interpreted in terms of the importance of selection mechanisms, since the omission of technology age as an explanatory variable could generate the negative duration dependence *per se*.[2] To our knowledge, the only previous empirical study of plant failure that disentangle different age effects is the study of Salvanes and Tveterås (1998), in which plant age is separated from capital age. It finds distinct and different effects from capital and plant age. It is not obvious to us, however, that the vintage of capital is a good proxy for the vintage of technology, as the introduction of new technology not necessarily can be captured by a single-dimensioned index like a capital vintage index. Our measure of technology age is based on the view that new technology can be introduced and implemented in a myriad of ways, which result in changes in the productivity level. Empirically we capture this by analyzing the plants' 'Solow-residual'.

Our empirical findings suggest that, besides industry-specific and regional labor market effects, insider mechanisms, the structure of human capital, as well as the different age effects are important determinants of plant failure. By and large the results conform to our *a priori* hypotheses.

The remainder of this paper is organized in the following way. It starts out with a general motivation for our research topic by presenting some evidence on the importance of plant turnover in Swedish Manufacturing in terms of its links to productivity growth (section 2). Section 3 puts our empirical analysis into the context of a theoretical model of plant failure that we develop. Section 4 describes the empirical counterparts of the variables in the theoretical model. Data and the statistical model are presented in section 5. The results from the empirical analysis is presented in section 6, before finally concluding in section 7.

[2] See Kiefer (1988); Lancaster (1990). The intuition behind this result is simple: Since plants with favorable technology on average will live longer, the mixture distribution will change over time so that the fraction of plants with favorable technology will increase as time goes by. Thus, the longer spells are overrepresented by plants with the low failure probability.

2 Plant Turnover and Productivity Growth

In this section we motivate our research topic by presenting some basic facts on how plant turnover and its components relate to productivity growth. (The implications on individuals, in terms of changes in income, employment status, etc., because of the reshuffling of jobs induced by plant turnover could have served as another motivation.) The close relationship between plant turnover and productivity growth is hardly a new idea, but has been around at least since the days of Schumpeter. For instance, the notion of creative destruction expresses the necessity to replace old technologies in order to adopt new ones, which often is assumed to be accommodated by plant turnover.

To get a feeling of how important this process might be, Table 1 presents the current average labor productivity[3] of plants that have entered within the $t-n$ period and of plants that will exit within the $t+n$ period, relative to the productivity of continuing plants, P_{en}/P_c and P_{ex}/P_c. The figures are annual averages and refers to the stock of Manufacturing plants in the 1985-96 period.

Table 1: Relative productitivity of entering and exiting plants[1]

	Entering plants			Exiting plants		
Time span	P_{en}/P_c	N_{en}/N	Effect[2]	P_{ex}/P_c	N_{ex}/N	Effect[3]
$t \pm 1$	0.97	0.03	-0.1	0.75	0.04	1.0
$t \pm 3$	1.03	0.06	0.2	0.76	0.12	2.9
$t \pm 5$	1.04	0.08	0.3	0.77	0.19	4.4

[1] The table reports the productivity in period t of plants that have entered (will exit) within the $t-n$ ($t+n$) period relative to the productivity of continuing plants in period t.

[2] Refers to the effect on the Manufacturing productivity in t (in percentage points) because entering plants differ in productivity from continuing plants in period t.

[3] Refers to the effect on the Manufacturing productivity in $t+n$ (in percentage points) because exiting plants differ in productivity from continuing plants in period t.

From the first row of entries, we learn that plants that have entered during the course of a year on average contribute negatively to the growth in Manufacturing productivity, as their productivity is somewhat lower relative

[3] Measured as the value-added per worker deflated by a three-digit level producer price index.

to the productivity of continuing plants. Plants that will exit within the next year on average contribute positively to the growth in Manufacturing productivity, as their productivity is substantially lower as compared to the productivity in continuing plants.

In the second and third row of entries, the time horizon is increased, so that an entering (exiting) plant is defined as a plant that has entered (will exit) within the $t-3$ ($t+3$) and $t-5$ ($t+5$) period, respectively. In the longer run, exiting as well as entering plants contribute positively to Manufacturing productivity growth. The productivity of plants that have entered within the last 3 and 5 years is actually higher relative to the productivity of continuing plants. The different results for the entering plants in the long and short run suggest that the returns to entry do not come immediately and/or that the less efficient entrants are sorted out in the longer run.

The effect on Manufacturing productivity growth is quite large in the longer run ($t\pm5$), partly because the employment shares, N_{en}/N and N_{ex}/N, get large as the time horizon is increased. The average labor productivity in Swedish Manufacturing would on average had been 0.4 percentage points lower if the entering plants had not entered and 4.4 percent lower if the exiting plants had not exited.

We end this section by concluding that the entry and, in particular, the exit of plants are important phenomena in the process of growth. Furthermore, the close relationship between the plant turnover and productivity growth indicates that the productivity of the plant is likely to be a good predictor of plant exit. However, based on these "raw" facts we are not able to discriminate between the various possible underlying forces of plant exit mentioned in the introduction, since most of them, in one way or another, are related to plant-level productivity.

3 A Model of Plant Failure

In order to fix ideas and to provide guidance for what variables to include in the empirical analysis, it is useful to consider a simple theoretical framework.[4]

We assume an economy in which plants produce slightly differentiated products that are sold in monopolistic competition.[5] In the short run labor

[4] See Hamermesh (1993) for an alternative model of plant failure. Also see Antelius and Lundberg (2000) for a study of the determinants of job reallocation across industries.

[5] By focusing on plants we assume that the important economic decisions are made at the plant-level, rather than at the firm-level. The empirical analysis is also conducted at

is the only variable factor of production. Production and the inverse demand function for a plant are assumed to be

$$Y = \varepsilon A L^{\alpha} = \varepsilon q \tag{1}$$

and

$$P = D q^{-1/\eta} \tag{2}$$

where $\varepsilon > 0$ is a stochastic productivity parameter with unit mean[6], $\alpha < 1$, D is demand index and $\eta > 1$. Apart from the stochastic productivity parameter, the parameters of production and demand are assumed to be the same for all plants within an industry.

In each period the plant is, with probability λ, exposed to an idiosyncratic productivity shock drawn from the distribution $f(\varepsilon)$. Conditional on the stochastic productivity component the plant will decide whether to continue operations and, if so, employment, output and prices.

According to equation (1) and (2) profit is given by

$$\pi = \varepsilon D q^{\kappa}(L) - wL \tag{3}$$

where $\kappa = 1 - 1/\eta$. Labor is assumed to be determined optimally at all times by the first order condition, such that the marginal revenue product equals the bargained wage rate or

$$L = (w/\alpha\varepsilon\kappa D A^{\kappa})^{-1/(1-\alpha\kappa)} \tag{4}$$

It is assumed that a plant exits the market if maximized current profits fall below a certain target profit value, π^*, or

$$\pi\left(L(\varepsilon)\right) \leq \pi^* \tag{5}$$

where $\pi\left(L(\varepsilon)\right)$ is obtained by inserting equation (4) in equation (3). For now on π^* is assumed to be exogenous, but possible determinants of the target profit value will be discussed later on.

According to the previous, the reservation productivity, ε^*, which solves $\pi(\varepsilon^*) = \pi^*$, expressed in logarithms, is

$$\ln\varepsilon^* = (1-\alpha\kappa)[\ln\pi^* - \ln(1-\alpha\kappa)] + \alpha\kappa[\ln w - \ln(\alpha\kappa)] - \ln D - \kappa\ln A \tag{6}$$

the plant-level. However, we also analyze single-unit plants (i.e. plants in which firm- and plant-level decision making coincide) separately.

[6] This shock can equally well be thought of as a demand shock or a combination of both without changing anything in the analysis.

and the implied probability that a plant will close, θ, is then

$$\theta = \lambda \int_0^{\varepsilon^*} f(\varepsilon) d\varepsilon = \lambda F(\varepsilon^*) \tag{7}$$

Equation (7) implicitly defines a relationship between θ and the arguments of π and π^*.

The engine of plant closures in this theoretical framework is unfavorable productivity (or demand) shocks, but how responsive a plant is to a shock depends to a large extent on industry-specific factors such as the parameters of production and product demand. Note that, so far, this model has no predictive power of which plants within a certain industry and region that are most likely to shut down. From comparative statics on equation (6) and (7) we learn that the probability of plant failure is higher the higher is the shock intensity, λ, the lower is the labor productivity, A, the lower is the product demand, D, the lower is the labor intensity, α, and the higher is the product market competitiveness, $\eta(\kappa)$. Also exogenous increases in wages, w, and in the target profit value, π^*, would increase the failure probability. However, we extend the model to allow for the possibility that these latter variables are determined endogenously and, thus, plant-specific explanations for within-industry differences in the failure probabilities across plants are introduced.

3.1 Wage Determination

Although the wage setting in the Nordic countries is often thought to be highly centralized, the wage setting process actually takes place at two levels, at the industry level (centralized) and in local negotiations (wage drift). Thus, industry- as well as plant-specific effects may both play important parts in wage determination. Another institutional feature that may be of importance is the strict employment protection legislation in Sweden, which, for instance, determines the order by which employees should be dismissed.

Based on these facts, we think it is appropriate to explicitly take into account that wages are determined locally in negotiations between the workers and the employers in our model. Also, we should consider the fact that not all workers face the same risk of being dismissed, because of the employment protection rules.

Wages are assumed to be determined in plant-level negotiations and the timing of the model is such that wages are set before the idiosyncratic shock is realized. Extending slightly to the model presented in Layard, Nickell, and Jackman (1991), we assume that the bargain over wages at the plant level is the one which maximizes

$$\chi = [(w - O)S]^{\beta}[\pi^{e} - \pi^{*}] \tag{8}$$

where w is the real wage, O is the worker's expected income if no agreement is reached and e denotes expectations. The owner of the plant is assumed to receive π^* in case of no agreement.[7] S is the probability of remaining in the same plant the next period given the outcome of the bargain. Only workers who remain in the plant from the previous period, L^I, are assumed to take part of the wage bargain and they only care about their own utility. More formally, if we define δ as the fraction of employees with no seniority (newly hired since the last period), then at any given point of time the number of insiders is given by $L^I = (1-\delta)L$. These assumptions then imply that the probability of remaining in the plant for an 'insider' is higher if the number of insiders is relatively small as compared to expected employment, (i.e. $S'(L^I/L^e(w)) < 0$).

Utilizing the envelope theorem, the bargained wage that satisfies equation (8) is

$$\frac{w-O}{w} = \frac{1}{-\frac{w}{s}\frac{\partial S}{\partial w} + \frac{wL^e}{\beta(\pi^e - \pi^*)}} \tag{9}$$

and with the previous assumptions about production and product demand, utilizing that $\eta_{Sw} = \frac{\delta S}{\delta w}\frac{w}{S} = \frac{\delta S}{\delta L}\frac{L}{S} * \frac{\delta L}{\delta w}\frac{w}{L} = \eta_{SL} * \eta_{Lw} = \eta_{SL} * (1-\alpha\kappa)^{-1}$ we arrive at the following expression for the wage mark-up over the outside option

$$\frac{w-O}{w} = \frac{1-\alpha\kappa}{\eta_{SL}(L^I/L^e(w)) + \left[\frac{\beta}{\alpha\kappa}\left(1 - \frac{\pi^*}{\pi^e}\right)\right]^{-1}} \tag{10}$$

where η_{SL} is the individual employee's elasticity of remaining in the same plant with respect to expected employment and with $\eta'_{SL} > 0$.[8]

We assume that the option value of the worker is given by $O = p(u)\overline{w} + (1-p(\ u))b$. $p(u)$ is the probability of remaining unemployed in the case of dismissal, being a function of the unemployment rate with $p' < 0$; $\overline{w}$ is the outside wage level and b the benefit level in case of unemployment.

[7] An alternative threat point of the owner, which simplifies matters but may be less realistic in the face of the previous discussion concerning the target profit, would be to assume that the owners receive nothing in case of no agreement.

[8] In the case where the plant owner's threat point is zero equation (10) reduces to the wage equation in partial equilibrium in Layard, Nickell, and Jackman (1991). This extension does not change any comparative statics.

Thus, with wage bargaining at the plant level, local labor market conditions, in terms of outside incomes and the probability to obtain a new job in case of unemployment, will also make a difference on the shut-down probability, since these factors affect the wage pressure. Furthermore, with the assumption made that only insiders take part of the wage negotiation, the share of insiders at the plant level will also affect the survival capacity of the plant, because the dismissal probability for an insider is affected by the composition of outsiders and insiders at the plant.

Working through the comparative statics of (6), (7) and (10) enables us to summarize the implications of the model by that the probability of plant failure is higher:

- the higher is the shock intensity in the industry, λ
- the greater is the union power, β
- the lower is the unemployment rate, u
- the higher is the relevant outside wage, $\overline{w}$
- the higher is the unemployment benefit level, b
- the smaller is the share of insiders in the plant as compared to current employment, L^I/L
- the higher is the target level of profits at the plant, π^*.

Furthermore, the probability of plant failure is indeterminate with respect to,

- the product market competitiveness, κ
- the labor intensity, α
- the product demand, D
- the common productivity level, A.

The latter effects are indeterminate to the extent that the direct effect on the reservation productivity is counteracted by an indirect effect working through wages. Consider for instance an increase in product demand: as a direct effect this will increase the likelihood to survive because of larger revenues, but this effect is counteracted, at least in the longer run, by the indirect effect working through higher wage pressure.

3.2 Endogenous Target Profit

It may very well be the case that the target value of profits, π^*, should not be regarded as exogenous either. Factors that may influence π^* could be more closely examined if the model would be formulated as a dynamic optimization problem. One such possible formulation of the target profit could be derived from a search model framework, in which potential entrepreneurs each period make an innovation corresponding to a specific value in the distribution of idiosyncratic shocks and then choose between becoming an operational entrepreneur or remain idle. Without providing any further details of the derivation (available upon request), one possible formulation of the target profit is

$$\pi^* = z - K - \frac{\lambda}{r + \lambda} \int_{\varepsilon^*} [1 - F(x)]\pi'(x)dx \tag{11}$$

where z is the alternative income of the owner of the plant; K sunk costs associated with plant entry and plant exit; and r is the discount rate. Then the target profit would be increasing in alternative incomes of the owner, decreasing in sunk costs associated with entry and decreasing in the option value of continuing production. The option value of continuing production, in turn, is higher the higher is the expected value of a shock, the less likely it is to be exposed to a shock and the lower the discount rate is.[9]

We consider a number of theoretical mechanisms, namely plant-specific human capital, selection mechanisms, and technology vintage effects, that could be thought of as affecting the shutdown condition through the determinants of the target profit level. We in the proceeding only discuss how these considerations may affect the shutdown condition through the determinants of the target profit (equation (11)).

Plant-Specific Human Capital

The acquisition of plant-specific human capital through training or learning-by-doing would generally increase the rents to be shared between the worker and the owners of the plant. Given that the extra rents generated are not fully captured by the workers (i.e. $\beta \neq 1$), this would provide a rationale for why plants intense in specific human capital exhibit a higher reluctancy to shut down operations (Oi, 1962; Becker, 1964).

[9] One should note that if the target profit is endogenously determined, then it is no longer possible to determine the sign of the effect of an increased shock intensity, λ, on the exit probability. As far as we can tell, this is not the case for any other variables in the model.

In terms of equation (11) investments in specific human capital could be thought of as increases in $\pi'(x)$. Thus, the option value of continuing operations increases and the target profit value, π^*, decreases, which in turn would decrease the reservation productivity, ε^*, and the failure probability, θ.

Another reason why the human capital structure of a plant may make a difference for the shut-down decision is if there are non-uniform (sunk) costs associated with the dismissal of workers. Higher dismissal costs decreases π^* (through higher K) and lowers the failure probability.

Selection Mechanisms

In Jovanovic's (1982) selection model, growth and survival of firms is the result of heterogeneity in the efficiency level across producers. Generally, the individual producer does not know the true cost relative to other competitors in the industry at the time of entry. (All producers have the same initial belief about the true $\pi'(x)$) In the selection process, the true efficiency relative to others is gradually unveiled via the outcome of production (which implies heterogeneity in π^* with respect to the relative efficiency level of the plant). This is a model of passive learning, in the sense that producers cannot influence its true efficiency level, but costliness upgrade its belief about their true level of efficiency in the production process.[10]

Technology Vintage effects

A partly competing hypothesis is derived from capital vintage models (e.g. Solow, 1956). The main point in capital vintage models is that capital of later vintages is more efficient than capital of older vintages. Technologies of various vintages will coexist because of sunk costs associated with the installation of new capital. The strength of vintage effect in an industry is dependent on the level of sunk costs and the degree of substitutability between factors of production. Industries with high sunk costs and low elasticity of substitution should be characterized by strong vintage effects and low turnover rates, while industries with low sunk costs and unstable relative input and output prices show high exit rates (Lambson, 1991).

[10] See Pakes and Ericson (1992) for an alternative model in which the assumption of passive learning is relaxed. Unlike the passive learning model, the producer can improve its position in the distribution of efficiency levels across plants through investments in research and development. Both these models predict that younger plants are more likely to exit than older plants.

Interpreted at the producer level we would expect higher exit rates among plants utilizing older technologies inferior to newer more efficient technologies. In terms of the determinants of the target profit level in equation (11), using technologies that become inferior relative to newer ones will reduce $\pi'(x)$ and the option value of continuing production (because wages are expected to increase through the workers' outside option value) and increase the alternative income of the owner, z (i.e., investing in a new plant becomes a more attractive alternative). Thus, the target profit level increases and the failure probability is expected to increase with the age of technology.

4 The Empirical Counterparts

The quest is to find the empirical counterparts to the variables motivated by theory in the preceding section. Here we briefly describe the variables included and put forward our hypothesis. Summary statistics, spell characteristics and exact definitions of the variables are found in Appendix 7.

As a measure of the shock intensity, λ, we include the job reallocation rate at the industry level. There are possibly two counteracting effects of an increased shock intensity. The direct effect is that the probability of exit increases, because the employers are more likely to be exposed to a bad outcome. The indirect effect, if target profits are assumed to be endogenous, is that the employers option value of continuing operation decreases, which lowers the exit probability.[11]

With respect to the parameters of the production function, we include the share of wage costs in the industry as a measure of α and as a measure of A we use the average labor productivity deflated by a producer-price index at the three-digit level.

With respect to the parameters of the product demand function: We include the 'Herfindahl index' as a measure of κ. With $\kappa \to \infty$ (perfect competition) the 'Herfindahl' index, which has been calculated as the squared sum of the plant's share of sales in the industry, is expected to approach zero and with $\kappa \to 0$ (monopoly) it would approach unity.[12] We construct

[11] It should be noted that job reallocation is likely to be dependent on not only the shock intensity in the industry *per se*, but also on the other parameters of production, demand and the wage bargain. Also the rate of job reallocation may approximate other factors, like the product life cycle and the pace of technological progress in the industry. Thus, this variable may serve as proxy for several factors and should be treated with some caution when interpreted.

[12] Ideally we would like to obtain measures also on the competion from abroad, which

industry-specific indexes of demand as a proxy for D, based on the development of average working hours per employee in the industries.

These considerations more or less cover the implications from the basic theoretical framework with exogenous wage and target profit determination, apart from some variables, such as unemployment benefits and union power, for which we either cannot obtain any good measures or do not have any variation to explore.

4.1 Measuring Wage Determinants

As a measure of the share of insiders in the plant $((L^I/L) = 1 - \delta)$, we include the share of employees who remained in the plant at least since the previous year. For instance, assume that employment in period $t-1$ is 15 and 10 in period t. If this employment change has been the resulting sum of 10 quits and/or layoffs and 5 hirings, then the share of insiders in period t would be 0.5 according to our definition. The outside options for a worker, O, is captured by including the average wage and the unemployment rate in the region. We expect the exit probability to increase as the share of insiders decreases and as the outside option for the worker increases, because of the effects on the wage pressure.

4.2 Measuring Determinants of the Target Profit

We include average plant size in the industry to approximate sunk costs and minimum efficient scale, having the hypothesis that the exit probability decrease with plant size. It should be noted that if sunk costs mainly are associated with capital in general our measure of the wage cost share may pick up the effects of sunk costs.

Theoretically we also argued that the plant-specific human capital, selection mechanisms and technology vintage effects affect the target profit value and, thereby, the failure probability.

Measuring Human Capital

We control for the human capital structure of the plant by including the average age in the workforce, the share of males, the share of Swedish citizens, the fraction of workers with university education and the fraction of workers with educations oriented towards technical subjects. Which types of labor that are intense in plant-specific human capital and/or are associated

we do not have in our data.

with high firing costs is pretty much an empirical question. Though, through longer experience, we expect that the degree of plant specificity in the human capital to be higher among older workers than younger. If highly educated workers and workers with educations oriented towards technical educations are more involved in the development of plant specific technologies, we may expect that there are larger quasi rents to be shared, and presumably lower probabilities of plant exit, in plants with workers with these characteristics.

Measuring Age Effects

In order to test the importance of selection mechanisms, i.e. that newly created plants face a higher risk of plant failure, we include plant age, which is simply measured as the number of years since plant entry. If selection mechanisms are important we would expect the exit probability to decrease with plant age.

Measuring the age of technology is clearly a more problematic task and deserves to be put in some focus. Capital vintage models differ with respect to how technology advances are implemented at the micro level. In some models (e.g. Caballero and Hammour, 1995), new technology is embodied in the plant and, thus, productivity advances is implemented through the entry and exit of plants. This type of capital vintage models has motivated the use of plant age as a proxy for the vintage of technology in empirical studies (Davis and Haltiwanger, 1990; Caballero and Hammour, 1996). This presumption probably has poor empirical support (Dunne, 1994). In other models technology advances takes place through investments in physical capital (Solow, 1956; Cooper, Haltiwanger, and Power, 1995; Greenwood and Jovanovic, 1998; Mortensen and Pissarides, 1998). This type of models have in turn motivated the use of capital vintage indexes as a proxy for technology age (Salvanes and Tveterås, 1998). However, the empirical support for this presumption is questionable as well.

Our view is that technology advances is implemented in a myriad of ways, for instance by changes in the human capital and in organization. This view is consistent with the view in Harberger (1998), where it is argued that aggregate productivity growth stems "from 1001 different sources". Therefore, we do not believe that the vintage of technology - which really is the concern of capital vintage models - can be captured along a single dimensioned measure like the vintage of physical capital, which furthermore is probably hard to measure with any greater accuracy. That is, new technologies may as well consist of new ways to organize production and not only of investments in new machines, which has been the traditional view. No matter what the underlying sources of technological change are, it is likely that they involve some degree of sunk costs and, thus, give rise to vintage effects if the input is subject to technology advances. Given that no set of measures probably ever can cover all the dimensions of new technology, it seems reasonable to base the measure of technology on its consequences rather than on its exact sources.

We conjecture that the introduction of new technology at the plant level is associated with changes in the plant-level productivity. However, not all changes in productivity is associated with technology vintage effects. In particular, new technology that is not associated with any sunk costs should not give rise to vintage effects. Since such technologies can be easily adopted by all plants without changing the relative productivity distribution across plants, we instead associate the introduction of new technology with changes in the plant-specific productivity level. That is, we decompose the state of technology, A_{et}, of a plant into the three components

$$A_{et} = A_t + A_{st} + \widetilde{A}_{et} \tag{12}$$

where A_t is the productivity component common to all plants at period t, A_{st} is the component common to all plants in the same industry and, finally, $\widetilde{A}_{et}$ is the plant-specific component of productivity.

Empirically we use the plant's average producer-price deflated labor productivity as a measure of A_{et}, from which we determine $\widetilde{A}_{et}$ by subtracting the corresponding aggregate measures.

There are at least four worries associated with such a approach. The idiosyncratic productivity component, besides technology, could also reflect: 1) the scale of operations, unless technology is characterized by constant return to scale; 2) the degree of capacity utilization; 3) the mix of inputs used in production; and 4) measurement errors, for instance unobservable inputs. To account for the degree of capacity utilization and scale effects, we require that the change exceed a certain threshold value in order to be associated with the introduction of new technology. Empirically the threshold value is chosen such that it represents a certain percentile in the distribution of idiosyncratic labor productivity changes. Our measure of technology age is defined as the number of years since the change in productivity exceeded a certain threshold value. To overcome the issue of changes in the mix of inputs an alternative approach could be to estimate the "Solow residual" of the plant, instead of using the "raw" idiosyncratic labor productivity component. The reason why this is not undertaken is that we deliberately want to keep our notion of technology broad, in the sense that changes in the scale of operations and mix of inputs by producers within the same industry facing similar conditions could very well be thought of as representing changes in technology. (Another important reason is that we lack data on important inputs other than labor, e.g. managerial skills and plant-level capital measures.) As a sensitivity analysis (reported in appendix) we experiment with different threshold values and with other identifying assumptions about when new technology is introduced. In particular we test the hypothesis that the results are caused by measurement errors and other temporary movements in productivity, by requiring long-lasting effects.

We expect the probability of plant failure to be decreasing in plant age and increasing in our measure of technology age.[13]

5 Data and Statistical Model

5.1 Data

This section describes data. More details on data and on how the analytical data set was created can be found in Appendix 7.

Our data set consists of information from three different data sources, namely *Manufacturing Statistics* ("Industristatistiken" or IS), the *Central Firm and Establishment Registry* ("Centrala Företags- och Arbetsställeregistret" or CFAR) and the *Regional Employment Statistics* ("Årlig regional sysselsättningsstatistik" or Årsys). IS contains plant-level information about almost the universe of plants in mining and Manufacturing (major division 2-3) over the 1970-96 period. (There are some restrictions with respect to the very smallest of plants.) IS has been merged with CFAR, which contains explicit information about the date of entry and the possible date of exit of all plants in the population, and with Årsys, which contains human capital information about the individuals in the plants from 1985-96. The linkage to CFAR has enhanced the quality of data, in the sense that we are able to discriminate between plants missing in data from true plant exits.

Our analysis is limited to the stock of plants in the 1991 and the inflow of plants in our observation period 1991-96, the period in which we have full information about the variables of interest.[14] This period covers a rather extreme recession as well as a peak. As compared to the period 1970-90,

[13] Becuase the complementarity between technologies of different vintages is likely to be decreasing in the age distance, this argument is true even for given profit levels and given sunk costs.

[14] Another reason why we limit the analysis to this period is changes in the population in IS in 1990 that are hard to handle longitudinally.

employment has never declined so fast as it did in the 1991-93 period and it has never increased by as much as it did in the 1994-96 period.

From the stock of plants in the 1991 we sample those plants that entered after 1972, which is the earliest year of entry that we can identify in CFAR. This implies that we observe spells as long as 24 years.[15] Of all different plants in our sample, 23 percent entered during our observation period. In total the analytical data set covers 22 998 observations on 7 228 different plants.

To fully understand the concept of plant failure, we stress that mergers, acquisitions, changes in ownership and so on will generally not result in plant failures in our data, unless the plant is actually physically shut down.[16]

5.2 Statistical Model and Maximum Likelihood Estimation

Data is such that we only observe whether a plant continues its operation or is shut down, but, of course, not the actual risk of plant failure. This is normally analyzed in limited dependent variable models, such as the logit or the probit model. We instead analyze data in terms of a discrete hazard model, since duration dependence is of interest in some of our specifications. However, in the case when time is of no interest the model generalizes to the limited dependent variable model known as the *Weibull probability model*.

The data in our analysis is interval censored, such that we only observe time to lie between a pair of consecutive follow-ups.[17] Time is divided into k intervals $[0, 1), [1, 2), \ldots, [q, \infty)$ where $q = k - 1$. In our analysis k is 24 years, which corresponds to the maximum number of years of a completed spell. The discrete hazard function is given by

$$\lambda\left(t|\mathbf{x}(t)\right) = \Pr(T = t|T \geq t, \mathbf{x}(t)), \quad t = 1, ..., q \tag{13}$$

where $T = t$ denotes failure in the $[t-1, t)$ interval and $\lambda\left(t|\mathbf{x}(t)\right)$ is the conditional probability of failure in that interval, given the interval is reached and given a vector of (possibly time-varying) covariates, $\mathbf{x}(t)$.[18] Correspondingly, the discrete survival function of the probability of *reaching* the $[t-1, t)$

[15] Because very few spells with a plant age of more than 20 years are observed, we treat those as having a plant age of exactly 20 years in the empirical analysis.

[16] The concept of a plant is defined only in terms of geographical location and production. (See SCB, Various years)

[17] Overviews of the econometric analysis using duration data can be found in Fahrmeir and Tutz (1994), Lancaster (1990), and Kiefer (1988)

[18] In fact, by failure in t we mean that the plant is not in existence at any time during $t+1$. This way we reduce possible problems with endogeneity and are able to measure the covariates with higher accuracy.

interval is

$$\Pr(T \geq t|\mathbf{x}(t)) = S(t|\mathbf{x}(t)) = \prod_{i=1}^{t-1}(1-\lambda(i|\mathbf{x}(i)). \tag{14}$$

To account for left-censored cases with known entry times, which is a feature of data, we need to modify (12) slightly. The conditional probability of reaching the $[t-1,t)$ interval for a left-truncated case must be conditional of having reached the censoring point. Thus,

$$\Pr(T \geq t|\mathbf{x}(t), T \geq s) = S(t|\mathbf{x}(t))/S(s|\mathbf{x}(s))$$
$$= \prod_{i=1}^{t-1}(1-\lambda(i|\mathbf{x}(i))/\prod_{i=1}^{s}(1-\lambda(i|\mathbf{x}(i)) = \prod_{i=s}^{t-1}(1-\lambda(i|\mathbf{x}(i)) \tag{15}$$

where s indicates the truncation point.[19] (For all non-left censored cases in the proceeding s equals zero).

Consider first the likelihood contribution of plant-failure in the $[t-1,t)$ interval. The unconditional probability of failure in the $[t-1,t)$ interval is given by the product of (6) and (13)

$$\Pr(T = t|\mathbf{x}(t)) = \lambda(t|\mathbf{x}(t))S(t|\mathbf{x}(t))/S(s|\mathbf{x}(s))$$
$$= \lambda(t|\mathbf{x}(t))\prod_{i=s}^{t-1}(1-\lambda(i|\mathbf{x}(i)) = \prod_{i=s}^{t}\lambda(i|\mathbf{x}(i))^{y_i}\prod_{i=s}^{t}\left[1-\lambda(i|\mathbf{x}(i))\right]^{1-y_i} \tag{16}$$

where $y_i = (y_{is}, ..., y_{it}) = (0, ..., 0, 1)$ for a non-censored case and where $y_{it} = 1$ indicates failure in the $[t-1,t)$ interval. Similarly the contribution of the right-censored observation is given by (13), which can be written as (16), but where $y_i = (y_{is}, ..., y_{it}) = (0, ..., 0)$. Summing over all n plants, the total log likelihood, assuming independence between individuals, is given by

$$l = \sum_{j=1}^{n}\sum_{i=s}^{t_j}\left[y_{ij}\log\lambda(i|x_{ij}) + (1-y_{ij})\log(1-\lambda(i|x_{ij})\right]. \tag{17}$$

Once a parametric model of the hazard function is chosen, it is straight forward to estimate (15) by maximum likelihood. We consider the proportional hazard model, which in continuous time is given by

$$\lambda_c(t|\mathbf{x}(t)) = \lambda_0(t)\exp(\mathbf{x}(t)'\gamma) \tag{18}$$

where λ_c denotes the continuous hazard function and where $\lambda_0(t)$ is the baseline hazard at time t and where γ is a vector of unknown parameters.

[19] How to handle left-truncated cases with known dates of entry is analyzed in Guo (1993)

The proportional hazard specification assumes that all covariates, including technology age, only have proportional effects on the baseline hazard, λ_0. The discrete counterpart of (18) is given by

$$\lambda(t|\mathbf{x}(t)) = 1-\exp[-\int_t^{t+1} \lambda_0(u)\exp\{\mathbf{x}(u)'\gamma\}du = 1-\exp(-\exp(\eta(t)+\mathbf{x}(t)'\gamma)) \tag{19}$$

where the second equality follows assuming constant hazard and covariates in each time interval and where $\eta(t) = \ln \int_t^{t+1} \lambda_0(u)du$. Inserting (19) into (15) gives us the following expression for the log likelihood to be estimated

$$l = \sum_{j=1}^{n}\sum_{i=s}^{t_j} \left[y_{ij}(1-\exp(-\exp(\eta_t + \mathbf{x}'_{ij}\gamma))) - (1-y_{ij})\exp(\eta_t + \mathbf{x}'_{ij}\gamma)\right] \tag{20}$$

If $\eta_t = \eta$, i.e. there is no duration dependence the expression is reduced to the likelihood function of the Weibull probability model (Greene, 1993).[20]

6 Results

Our empirical strategy is to estimate versions of the empirical equivalent to equation (7), which defines a relationship between the probability of plant failure and the arguments of profit and target profit. We first estimate our basic model of plant failure assuming that wages are exogenous. After having rejected the hypothesis that wages are exogenous, we then successively add to our analysis the effects of endogenous wage and target profit determination.

The results (not reported) from the model in which plant-level wages are assumed to be exogenous are implausable, in the sense that higher wages are associated with lower failure probabilities. A likely interpretation of this result is that higher plant-level wages reflect larger rents to be shared between the workers and the owners of the plant. Higher wages could of course also reflect differences in the human capital structure of the plant that may have an influence on the failure probability and which we do not control for.

To control for differences in the human capital structure across plants and to test for the assumed exogeneity of wages, we first estimated a simple plant

[20] Apart from the less familiar Weibull probability model, we have estimated our specifications as logit models, but since the results do not differ substantially we do not comment on those.

level wage equation by ordinary least squares and then inserted the plant level wage measure together with the predicted residual from the first stage wage equation in the exit equation (specification (i) of Table 2).[21] Variables denoted by s are specific to the 18 industries in our data, those denoted by r are specific to the 24 regions used and those denoted by e are specific to the plant. Under the hypothesis that wages are exogenously determined, the effect of the residual is expected to be zero. However, this model suggests that wages are not exogenously determined, since the effect of the predicted residual is negative and highly significant, i.e. higher unexplained wages are associated with a lower failure probability. Thus, we reject the hypothesis of exogenously determined wages.[22]

6.1 Industry Effects and Endogenous Wage Determination

In specification (ii) in Table 2 we report the results from a model in which wages are assumed to be endogenously determined and, thus, the plant-level wage measure is replaced by a measure for the outside wage, as defined previously. Furthermore, it is assumed that the unions are egalitarian (i.e. unions that care equally for insiders and outsiders) and thus we do not include the insider share variable.

All estimates are statistically significant and conform to our *a priori* hypotheses. The probability of plant failure is higher for plants in industries characterized by high job reallocation rates, which is our proxy for the shock intensity in the industry.[23] With respect to the parameters of the production function, our estimates suggest that failure risk is higher, the lower is the wage cost share and the lower is the average labor productivity. Correspondingly, for the parameters of demand function, the risk is higher, the more competitive the industry is and the lower the product demand is, as measured by the Herfindahl index and working hours, respectively. The risk of plant closure increases with the local wage level and decreases with

[21] The dependent variable in the wage regression is the logarithm of the deflated average wage cost in the plant and the included human capital variables are: average age and age squared of the workers, fraction of males, fraction of workers with Swedish citizenships, fraction of workers with university education and fraction of workers with educations oriented towards technical subjects.

[22] One could of course argue that unobserved differences in the human capital structure that are correlated with the failure probability is the main cause for the results, rather than endogenous wages. However, if we to the first stage equation add fixed plant effects, the sign and significance of the residual in the exit equation are virtually unchanged.

[23] There might be endogeneity problems associated with this variable, but at least it does not make any difference whether plant reallocation induced by plant turnover is excluded from our job reallocation measure or not.

the local unemployment rate. We like to interpret this as that when the option value of the workers increases this results in higher wage pressure which reduces the survival capacity of the plant.

Table 2: Determinants of plant exit with insider wage determination

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variable	Parameter estimates					
Job reallocation$_s$ (λ)	**5.294**	**2.631**	**2.612**	**2.399**	-0.406	-0.844
	(0.564)	(0.618)	(0.619)	(0.623)	(0.788)	(0.918)
Wage cost share$_s$ (α)	-0.096	**-0.855**	**-0.926**	**-0.992**	-0.491	-0.321
	(0.344)	(0.361)	(0.361)	(0.362)	(1.550)	(1.591)
ln(Labor prod.$_s$) (A)	**-0.216**	**-0.684**	**-0.746**	**-0.793**	*-0.619*	0.015
	(0.085)	(0.133)	(0.133)	(0.133)	(0.455)	(0.497)
Herfindahl index$_s$ (κ)	**-5.313**	**-2.468**	**-2.303**	*-1.880*	-2.317	-4.185
	(1.291)	(1.312)	(1.311)	(1.319)	(6.511)	(6.809)
ln(Working hours$_s$) (D)	0.018	**-0.391**	**-0.432**	**-0.447**	**-3.511**	**-3.293**
	(0.175)	(0.183)	(0.183)	(0.184)	(0.589)	(0.625)
ln(Avg. plant size$_s$) (π^*)	**0.117**	**-0.144**	**-0.144**	**-0.119**	**-1.451**	**-0.890**
	(0.051)	(0.057)	(0.057)	(0.057)	(0.414)	(0.453)
ln(wage$_{e/r}$) (w)	*0.332*	**0.649**	**0.741**	**0.823**	**2.132**	*0.911*
	(0.206)	(0.131)	(0.131)	(0.132)	(0.506)	(0.579)
Wage residual	**-0.274**					
	(0.043)					
Unemployment$_r$ (u)		**-4.397**	**-3.698**	**-3.785**	**-7.485**	*-8.326*
		(0.565)	(0.564)	(0.564)	(1.407)	(5.413)
Sh. of insiders$_e$ (L^I/L)			**-0.613**	**-1.588**	**-1.578**	**-1.576**
			(0.046)	(0.047)	(0.048)	(0.048)
Industrial dummies	no	no	no	no	yes	yes
Regional dummies	no	no	no	no	yes	yes
Time dummies	no	no	no	no	no	yes
Log likelihood	-8403	-8366	-8287	-7945	-7853	-7843

Standard errors are reported within the parentheses. Parameter estimates in **bold** (*italics*) idicate significance on the 5- (10-) percent level.

All specifications also include a constant.

In specification (i) the (time-varying) wage measure is specific to the plant and in specifications (ii)-(vi) it is specific to the region. See text for details.

In specification (iii) we test the hypothesis that insider wage determination is of importance by including the measure of the share of insiders in the plant. The parameter estimate of the share of insiders suggests that there are also important elements of insider mechanisms in wage bargaining. The magnitude is such that a 10 percentage point increase in the share of insiders in the plant reduces the failure probability by some 5 percent. We like to interpret this as that when the share of insiders in a plant is low, then the *ex ante* risk of loosing the job is lower for an insider and the insiders therefore exert higher wage pressure.

However, we are at risk of underestimating the importance of insider mechanisms if plant exit is a long-lasting process in which employment is gradually decreased until exit, which then endogenously would create a large fraction of insiders in plants about to exit the market. To, at least partly, test the importance of this we replace our insider-share measure by the average share of insiders in the plant (excluding the possible year of exit). Now, the parameter estimate of the insider share changes quite a deal. The implied magnitude is such that a 10 percentage point increase in the share of insiders in the plant reduces the failure probability by some 8 percent. In the proceeding we use the plant average insider share as the insider share measure.

Common for the previous specifications is an underlying assumption that all differences between industries and regions are captured by the included variables. In column (v) we check the robustness of the previous results when we in addition control for fixed regional and industrial effects. This reduces the significance of many of the industry variables, although the effects of the local labor market conditions and the share of insiders at the plant level remain intact. It should be noted, though, that this specification probably is over-parameterized, since there is little variation in data across industries and regions to explore in order to identify the effects of the aggregated variables.

In column (vi), as compared to (v), we add a full set of time dummies. As expected this has an impact on the significance of some of the presumably trended variables, such as unemployment, productivity and wages.[24]

In short: Our results suggest that endogenous wage determination are of importance in explaining plant failure, in the sense that the effects of the worker's outside option and the effect of the insider share at the plant are robust throughout the various specifications. The results on the industry variables also support our *a priori* hypotheses, but they are not robust

[24] Instead of time dummies we have tried capturing the effects of the business cycle by including the net employment change at the industry level. However, no major differences were found as compared to using time dummies.

against the inclusion of a full set of industry dummies.

Additional sensitivity analyses have been performed by the inclusion of controls for various initial conditions, such as the plant's size at the time of entry[25] and whether the plant was created as a part of an already existing firm or not, but these extensions do not change results in any substantial ways and, thus, they are not reported. Also, in the analysis we have excluded the mining industry and multi-plants (i.e. plants in which firm- and plant-level decision making do not coincide) , but we find no major changes in results.

6.2 Human Capital Effects

We have argued that differences in the human capital structure could be one potential source of heterogeneity across plants. Either because these differences also reflect differences in the degree of plant-specific human capital or because they reflect differences in firing costs. Another motivation why we should control for the human capital at the plant level is that our previous results regarding the effects of the insider share could be spurious, in the sense that the variable could approximate plant specific human capital.

In column (i) of Table 3 we add plant-level human capital measures to specification (v) of Table 2. The estimates of the aggregated variables are surpressed, since they remain by and large unchanged as compared to column (v) in the previous table.

The inclusion of human capital variables do not change the estimated effect of the insider share. Somewhat surprisingly, although the *a priori* expectations regarding these variables are not all that clear, we do not find any strong effects of the human capital structure of the plant, except for the fraction of workers with Swedish citizenship. One could perhaps argue that the latter variable correlates positively with experience in the Swedish labor market, but it is open question what the exact mechanisms generating the results are. The estimates may reflect the fact that when a plant is about to shut down, the employer ranks among the employees when firing, such that the most "valuable" workers are fired last. The employer protection legislation in Sweden may contribute to this, especially with respect to the estimate of the mean age of the worker. To partly, but not fully, overcome this potential problem the human capital measures are averaged over the plant's life time (excluding the possible year of failure), as was done with the insider share variable.

[25] This variable could be motivated to include as a proxy for plant-level capital, for which we do not have any measurs on.

Table 3: Determinants of plant exit including human capital and age effects

	(i)	(ii)	(iii)	(iv)	(v)
Variable	Parameter estimates				
Sh. of insiders$_e$ (L^I/L)	**-1.582**	**-1.555**	**-1.529**	**-1.551**	**-1.267**
	(0.048)	(0.051)	(0.052)	(0.053)	(0.053)
Age$_e$	0.001	0.001	0.001	0.004	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Man$_e$	-0.098	-0.101	-0.087	-0.079	*-0.205*
	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)
Swedish$_e$	**-0.474**	**-0.475**	**-0.459**	**-0.418**	**-0.711**
	(0.146)	(0.146)	(0.146)	(0.145)	(0.144)
University$_e$	-0.123	-0.126	-0.116	-0.138	*0.164*
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
Technical$_e$	*0.185*	*0.184*	*0.175*	*0.156*	**0.385**
	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)
Plant Age$_e$		-0.004	**-0.011**	**0.033**	0.023
		(0.003)	(0.004)	(0.014)	(0.018)
(Plant Age)$_e^2$				**-0.002**	0.001
				(0.001)	(0.001)
Tech Age$_e$			**0.017**	**0.055**	**0.105**
			(0.005)	(0.015)	(0.020)
(Tech Age)$_e^2$				**0.004**	**0.005**
				(0.002)	(0.002)
(Plant Age*Tech Age)$_e$				**-0.007**	**-0.009**
				(0.002)	(0.002)
Log likelihood	-7838	-7836	-7830	-7806	-7920

Standard errors are reported within parentheses. Parameter estimate in **bold** (*italics*) indicate significance on the 5- (10-) percent level.
The surpressed parameters are the same as in specification (v] of Table 2.

6.3 Plant and Technology Age Effects

Implicitly, so far, it has been assumed that the risk of plant failure exhibits no duration dependence. However, as was argued previously there are good reasons to believe that various age effects are important sources of plant heterogeneity. Furthermore, the previous estimates of the insider share are at risk of being biased because young plants by construction have a large fraction of "outsiders".

For illustrative purposes we have estimated the effects of plant and technology age semi-parametrically, by allowing for piece-wise constant effects, without any other covariates than industrial and regional dummies. The result is illustrated in Figure 1 where the hazard rate with respect to plant age is evaluated at different "technology ages". The result with respect to the age of the establishment conforms to what has been found in previous studies, namely that the risk of plant failure is decreasing in the age of the plant. This could be interpreted in terms of the importance of selection mechanism, but an alternative hypothesis is that omitted variables (other than technology age, industrial and regional effects) generate the negative duration dependence. Also, there seems to be important effects of the technology age, such that the likelihood of plant closure is higher the older technology being used.

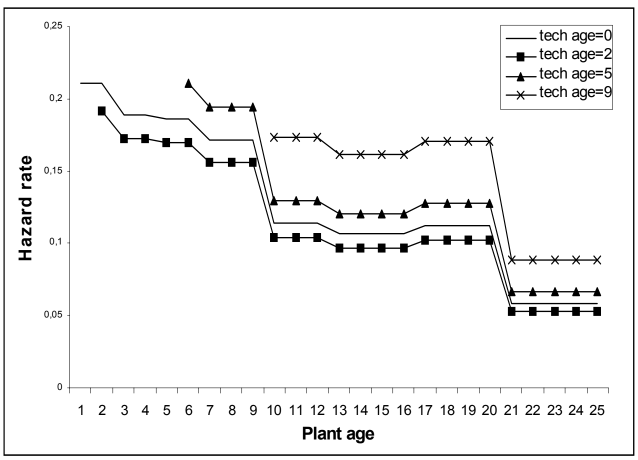

Figure 1: Baseline hazard functions evalutated at different technology ages

In column (ii) of Table 3 we add a linear effect of plant age to the previous specification. Although negative, the linear effect of plant age on the failure probability is not statistically significant. It should be noted that the inclusion of plant age does not affect the point estimate of the share of insiders.

When we in column (iii) add our measure of technology age the effect of plant age is significantly negative. The estimate of plant age suggests that a newly created plant faces an 11 percent higher risk of plant failure as compared to a plant that has been in existence for 10 years. The hazard is increasing in our measure of technology age, which then lends some support

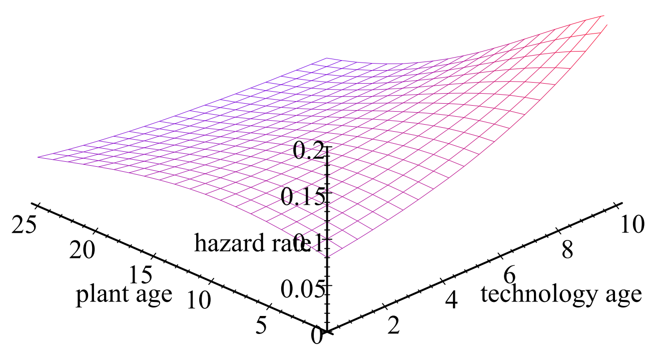

Figure 2: The hazard function with respect to plant and technology age according to specification (iv) in Table 3 where the rest of the covariates are set at their mean value.

to technology vintage models. For instance, the results imply that utilizing technology with an estimated age of 10 years relative to new technology increases the probability of plant failure by 19 percent.[26]

The result in column (iv), in which we add an interaction term between plant and technology age and second degree polynomials of plant and technology age, indicates that the effects of plant and technology age are not independent from each other. The estimates of the effect of plant age suggest that the risk of plant failure increases until approximately the eighth year of the plant's life time and thereafter the risk decreases. This pattern is not contradicted by the prediction from the theory of selection (Jovanovic, 1982). The hazard rate with respect to plant age is also more decreasing the older technology used. The hazard rate with respect to technology age, on the other hand, is increasing at an increasing rate. The relationship between the hazard rate, plant age and technology age from column (v) of Table 3 is perhaps best illustrated in a three dimensional plan (Figure 2).

As our theoretical model is specified, the employment and the exit decisions are simultaneously undertaken and what we estimate is a reduced form of plant failure in which employment has been replaced by its determinants. However, it can be argued that some of the variables used in the estimation are partly determined by current employment. If this would be the case, our estimates are at risk of being contaminated by endogeneity bias. For instance, it has been argued that smaller plants utilize temporary employment to a larger extent than larger plants do. If this is correct, the effect of the share of insiders at the plant partly captures the effect of the endogenously determined current plant size. Also, the definition of our technology age measure involves the volatility in plant-level productivity, which is likely to be decreasing in plant size. Thus, there might be a spurious positive correlation between technology age and plant size.

To overcome possible bias resulting from this, we in specification (vi) replace the plant-level measures by their size-orthogonal equivalents (except for plant age, which is a truly exogenous variable). That is, we instead use the residuals from an ordinary least squares regression of the plant-level variables on current employment. Indeed, the results change somewhat. The effect of the insider share is reduced, but it is still highly economically and statistically significant; the effect of technology age is reinforced by the "size correction", as expected; the hazard is still decreasing in plant age, but the shape is somewhat different from the previous specification; the effects

[26] The qualitative results are about the same if we instead model the age effects semi-paremetrically, by allowing for piece-wise constant effects.

from the plant-level human capital structure tell us, in addition to what was previously found, that the failure probability is higher the lower the fraction of men in the work force is and the more educated the work force is.

In short: Our results indicate weak and mixed effects of the plant-level human capital structure on the failure probability. We find support for selection mechanisms in the sense that older plants have lower failure probabilities, *ceteris paribus.* We also find strong support for technology vintage effects. In Appendix 7 we show that our main conclusion regarding technology age is not very sensitive with respect to various assumptional changes about how technology age is measured. Still, admittedly there are remaining uncertainties surrounding what our technology age measure exactly reflects and, therefore, we stress that this effect should be interpreted with some caution.

7 Conclusions

Despite a growing literature on producer heterogeneity, its exact sources are not very well explored. In the face of this, the main contribution of this paper is that we address the empirical importance of a number of potential such plant-specific sources by studying the determinants of plant failure on a sample of establishments in the Swedish mining and Manufacturing industries over the 1991-96 period.

From our theoretical framework we test hypotheses regarding the linkages between the probability of plant closure and industry specific characteristics of production and product demand. The results do at least not contradict what we can expect from our theoretical framework. Nevertheless, a model including only variables reflecting characteristics of the industry and the region is of limited interest, since it has no predictive power of why certain plants within a specific industry and region face higher risks of failure than others and, thus, do not add very much to our understanding of the sources of producer heterogeneity at the micro level.

However, we argued theoretically that insider mechanisms in wage determination may be one potentially important source of heterogeneity in the risk of plant failure across plants. If only insiders take part in the plant-level wage negotiation, then a low fraction of insiders relative to expected employment in the plant implies an increased wage pressure, since the risk for an insider of being laid off is relatively low. This in turn would increase the risk of plant failure. Our empirical analysis indeed suggests that this is the case and that the result seems to be quite robust to alternative hypothesis. The order of magnitude is such that if the share of insiders in the plant increases by ten percentage points, then the probability of plant closure decreases by approximately eight percent.

Another potential source of producer heterogeneity that we have addressed is differences in the structure of human capital across plants. However, we find weak effects from the variables reflecting the human capital structure of the plant. On the other hand, it is neither clear cut what we should expect *a priori* from these variables.

Previous studies have also looked upon the importance of selection mechanisms by studying the hazard rate with respect to plant age. We address this source of heterogeneity as well, but unlike most previous studies we also make an attempt to disentangle and empirically test the importance of plant and technology age. (The access to spells that are much longer than most previous studies makes the analysis of the latter effect meaningful). In accordance to what has been previously found, our results suggest that selection mechanisms are of importance, in the sense that older plants have lower failure probabilities.

There is also evidence that the hazard of plant failure is increasing in our technology age measure, thus, lending some support to the hypothesis stemming from the capital vintage literature that plants utilizing old technologies are more likely to shut down.

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Appendix

This appendix serves two purposes: 7 describes how the analytical data set was constructed along with definitions and summary statistics of the most important variables used in the empirical analysis. One crucial assumption in our analysis is how technology age is measured. Therefore we in 7 conduct some sensitivity analysis in order to give some indications on how robust our previous conclusions are.

The Analytical Data Set and Variables

Our analysis is limited to the stock of existing plants and the inflow of entrants in mining and Manufacturing industries during the 1991-96 period. From this sample in *Manufacturing Statistics* (IS) we have made a number of restrictions that deserve to be put in focus. First of all we have excluded all plants in existence prior to 1972, which is the earliest year of entry that we can identify in the *Central Firm and Establishment Registry* (CFAR). Human capital information has been appended to the analytical data set through a linkage between IS and the *Regional Employment Statistics* (Årsys). A number of observations had to be excluded from the analytical data set because the match quality was not satisfying, evaluated by comparing the employment and changes in employment according to the two data sets. Because of missing information on human capital variables we have imputed (through extrapolation) values in some cases, where it has been regarded as possible, while deleted observations in other cases, in which the basis for imputation was not satisfying (i.e. when we would have had to impute more than 3 consecutive values). All in all, we had to exclude some 5 percent of the plants from the original sample because of poor match quality or because of missing information, and we had to impute human capital information values in some 7 percent of the remaining cases.

- Job reallocation (λ) in the industry in period t is calculated as the sum of the number of jobs created and destroyed across plants between $t-1$ and t divided by the average number of jobs in the industry.

- The wage cost share (α) is measured as wage costs over total input costs in the industry.

- Productivity (A) is measured as the average labor productivity in the industry deflated by a producer price index at the three-digit level. This variable is transformed into logarithms.

- The Herfindahl index (κ) is measured as the sum of the squared shares of plant sales in the industry.

- Working hours (D) is measure as average working hours (in 1000) per workers and year. This variable is transformed into logarithms

- Average plant size (π^*) is measured as the average number of employees in the plants in an industry.

- Wage (w) is measured as the average, producer-price deflated, wage-costs in the region (corresponding to "län"). This variable is transformed into logarithms.

- The unemployment rate (u) is measured as the total (openly unemployed and in labor market programs) unemployment divided by the labor force in the region.

- The share of insiders ($(L^I/L) = 1 - \delta$) in the plant is measured as the fraction of employees in period t that were also employed by the same plant the previous year.

- The age of the employees in each plant (Age) is expressed as an average over the number of employees and over the plant's existence, excluding the possible year of failure. This variable is divided by 100.

- The number of men (Man); individuals with Swedish citizenship ($Swedish$); individuals with more education than high school ($University$); and individuals with an education within the engineering programs, either in high school or in the university, ($Technical$), are expressed as fractions.

- Plant age ($Plant\ Age$) is defined as the number of years since plant entry.

- Our preferred measure of technology age ($Tech.\ Age$) is defined as the number of years, since the last time the change in the idiosyncratic labor productivity exceeded a threshold value. In our preferred specification we compare the productivity in t with that in $t-1$ and use the 90:th percentile in the distribution of idiosyncratic labor productivity changes as our threshold value.

Sensitivity Analysis with Respect to how Technology Age is Measured

Our measure of technology age is based on the idea that the introduction of new technology can be determined by analyzing the "Solow residual". However, how large the change in the Solow residual must be in order to represent the introduction of new technology is arbitrarily chosen. Therefore, it is of interest to find out whether our results are robust against choosing different threshold values.

Our preferred measure of technology age was constructed such that new technology was identified when the annual change in the idiosyncratic productivity exceeded the 90:th percentile in the distribution of annual changes in plant-level productivity (see the first column of Table A-3). The second column shows how the age parameters change when a much lower percentile value (the 25:th) is chosen. The remaining covariates throughout Table A-3 coincide with specification (v) in Table 3. In the third and fourth column we have used the absolute change in the idiosyncratic productivity with different threshold values. This is done in order to capture the idea that also negative changes could reflect the introduction of new technology, because of a possibly long lasting retooling process. Finally, in the fifth and sixth column, we test the hypothesis that the results are caused by temporary movements (or possible measurement errors) in the idiosyncratic productivity. That is, contrary to previous specifications, we require the shifts in the productivity to have permanent effects, in the sense that we compare average lag and lead productivity for each year of the plants' life-time and if the difference exceeds the threshold value in the distribution of changes then we identify the introduction of new technology. Needless to say this procedure may introduce new problems, since our measure now is conditional on future events.

The results in Table A-3 show that the estimated effects are somewhat sensitive with respect to how technology age is measured, in the sense that the effects of plant age and that the exact functional form of the relationship between the age effects and the hazard vary between the specifications. However, the main conclusion - that the hazard is increasing in technology age - seems to be robust against these different measures considered.[27]

[27] Neither do the surpressed parameters (see Table 3, column (v)) change in any significant ways.

Table A-1: Summary statistics of variables

Variable	Mean	Std. dev.	Min	Max
Job reallocation$_s$	0.163	0.037	0.066	0.312
Wage cost share$_s$	0.369	0.097	0.166	0.526
ln (productivity)$_s$	4.458	0.349	3.876	5.444
Herfindahl index$_s$	0.017	0.019	0.004	0.139
ln (working hours)$_s$	1.009	0.194	0.571	1.327
ln (average plant size)$_s$	3.450	0.605	2.026	4.994
ln (wage)$_r$	3.777	0.287	3.773	4.487
Unemployment$_r$	0.102	0.038	0.025	0.183
Share of insiders$_e$	0.669	0.364	0	1
Age$_e$	38.627	5.275	20.333	66
Male$_e$	0.750	0.212	0	1
Swedish$_e$	0.907	0.122	0	1
University$_e$	0.132	0.154	0	1
Technical$_e$	0.395	0.218	0	1
Plant age$_e$	9.257	6.735	0	24
Tech. age$_e$	4.038	5.146	0	24
# of obs.	22998			

The table shows the summary statistics of the transformed variables, as used in the empirical analysis. Foot index s denotes variables that are specific to the industries, r variables specific to the regions and e variables specific to the plants.

Table A-2: Spell characteristics of plant age

Plant age	Censoring	Failures
0	150	196
1	210	279
2	210	266
3	224	194
4	310	222
5	429	182
6	201	135
7	168	145
8	202	142
9	166	105
10	172	101
11	185	97
12	187	82
13	146	83
14	139	54
15	156	56
16	118	93
17	79	81
18	116	82
19	116	81
20	244	53
21	116	35
22	207	16
23	91	3
24	101	2
Sum	4443	2785

The table shows the distribution of plantfailure and censoring by plant age.

Table A-3: The impact of different measures of technology age

	Temporary				Permanent	
Threshold (percentile)	90:th	25:th	abs(90:th)	abs(25:th)	90:th	25:th
Variable	Parameter estimates					
Plant age	*-0.022*	**-0.024**	0.003	0.001	**-0.204**	0.009
	(0.014)	(0.012)	(0.014)	(0.012)	(0.026)	(0.012)
(Plant age)^2	0.000	-0.001	-0.001	**-0.002**	**0.006**	**-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Tech. age	**0.070**	**0.101**	**0.032**	**0.054**	**0.244**	**0.041**
	(0.015)	(0.016)	(0.014)	(0.019)	(0.025)	(0.017)
(Tech. age)^2	**0.007**	-0.002	**0.019**	**0.023**	**-0.008**	**-0.011**
	(0.015)	(0.003)	(0.003)	(0.008)	(0.003)	(0.002)
Plant age*Tech. age	**-0.011**	-0.001	**-0.021**	**-0.024**	0.000	**0.010**
	(0.002)	(0.003)	(0.003)	(0.008)	(0.003)	(0.002)
Log likelihood	-8095	-8076	-8090	-8104	-7957	-8088

Standard errors within parentheses. Parameter estimates in **bold** (*italics*) indicate significance on the 5- (10-) percent level.

In addition, all specifications include controls for the same variables that appear in specification (v) of Table 3.

"Temporary" refers to the analysis of the annual change in the idiosyncratic productivity and "Permanent" refers to the difference between the lag and lead mean productivity throughout the plant's life-time for each year.

Essay III

The Spatial Wage Distribution, Sorting of Workers and Urban Agglomeration

The Spatial Wage Distribution, Sorting of Workers and Urban Agglomeration*

1 Introduction

The concentration of economic activities is one of the most striking features of the economic landscape. For instance, according to the 2000 Decennial Census the most economically active counties in the U.S., accounting for 50% of employment, only account for less than 3% of land; and the least economically active counties, accounting for 50% of land, only employ less than 2% of the U.S. workforce. Agglomerated regions are also areas where wages are generally higher than elsewhere – Glaeser and Mare (2001) report

*This document reports the results of research and analysis undertaken by the U.S. Census Bureau staff. It has undergone a Census Bureau review more limited in scope than that given to official Census Bureau publications, and is released to inform interested parties of ongoing research and to encourage discussion of work in progress. This research is a part of the U.S. Census Bureau's Longitudinal Employer-Household Dynamics Program (LEHD), which is partially supported by the National Science Foundation Grant SES-9978093 to Cornell University (Cornell Institute for Social and Economic Research), the National Institute on Aging, and the Alfred P. Sloan Foundation. The views expressed herein are attributable only to the author(s) and do not represent the views of the U.S. Census Bureau, its program sponsors or data providers. Some or all of the data used in this paper are confidential data from the LEHD Program. The U.S. Census Bureau is preparing to support external researchers' use of these data; please contact John M. Abowd (John.Abowd@cornell.edu), U.S. Census Bureau, LEHD Program, FB 2138-3, 4700 Silver Hill Rd., Suitland, MD 20233, USA. The author gratefully acknowledge comments and useful suggestions from Karolina Ekholm and seminar participants in Uppsala University.

a 33% wage premium for workers in cities – and in sharp contrast to basic economic theory, the spatial wage differences are not arbitraged away by either movements of workers or relocation of firms. This paper studies the forces of urban agglomeration that make the spatial wage differences persist over time.

I approach this issue by an empirical test of a spatial labor demand model, due to Krugman (1991) and Helpman (1998). The main idea of the model is that urban agglomeration arises as a result of increasing returns to scale in combination with the existence of transportation costs.[1] On the one hand, firms have an incentive to locate in densely populated areas where large markets can be accessed at low transportation costs. Congestion and higher costs of living, on the other, act as centrifugal forces as firms have to compensate workers for higher costs of living in dense areas. The implied wage structure is such that firms pay higher wages in locations where the income in surrounding locations is high, where transportation costs to these locations are low, and where the prices of competing traded goods in these locations are high.

I extend the model to take into account the effects of heterogeneity in transportation costs and sorting of heterogeneous workers. When I estimate the model using micro data from the U.S. Census Bureau's LEHD Program, I find strong support for urban agglomeration effects on firms' pay and the fraction of variation in earnings that can be explained by spatial factors is substantial. The parameter estimates are consistent with the idea in the theoretical model that increasing returns to scale and transportation costs are driving forces of urban agglomeration. Furthermore, the estimates reject that transportation costs are homogenous across industries and the results suggest that high-transportation costs industries sort into urban areas.

The next section briefly reviews the previous literature and discusses the contributions of this study. In Section 3 the main elements of the theoretical model is presented. Section 4 describes the empirical model. Section 5 presents the LEHD data. Section 6 provides descriptive results. The analytical results are presented in Section 7. Finally, Section 8 concludes.

[1] See next section for alternative explanations for urban agglomeration.

2 Background

2.1 Urban Agglomeration and Spatial Effects on Pay

Casual observation and ample empirical evidence show that production and consumption as well as other measures of economic activities are very unevenly distributed in the spatial dimension. The contribution of most regions to statistical aggregates is substantially smaller than their relative geographic size, regardless whether the focus is across countries or across regions within a country. Instead, a bulk of production and consumption can be attributed to a few regions accounting only for a fraction of land.

Urban agglomeration is also associated with higher wages; it is common practice in the labor literature to include big city dummies that usually are associated with positive wage premia. The previously mentioned study by Glaeser and Mare (2001) finds that the log of the population can explain 60% of the variation in wages across cities and that there is a 33% wage premium associated with living in cities – a wage premium which is larger than what is usually associated with gender or race.

Why these spatial wage differentials, which are persistent, are not arbitraged away by either movements of workers or relocation of firms is a key question in understanding the forces of urban agglomeration. The study of Glaeser and Mare finds little evidence of spatial wage differentials, once nominal wages are adjusted for differences in costs of living across regions. Thus, differences in costs of living may be responsible for why equalization of spatial wage differentials does not come about through worker reallocation. However, this does not explain why firms concregate towards urban areas, instead of locating where labor is cheap.

The idea that producers, other things being equal, prefer locations with good access to customers has served as the basis for market potential studies. The typical market potential function measures the potential of one location r, as the sum of purchasing power of all other sites s, weighted by the distance to these sites.

$$M_r = \sum_s \frac{1}{D_{rs}} P_s \tag{1}$$

where D_{rs} is the distance from r to s, and P_s is the purchasing power at s. The classical study was by Harris (1954), who used the market potential framework in an attempt to explain the concentration of manufacturing firms in the *Manufacturing Belt* in the United States.[2] However, the *ad hoc*

[2] See also Clark, Wilson, and Bradley (1969), Dickens and Lloyd (1977), and Keeble, Owens, and Thompson (1982).

nature of this approach has prevented it from becoming a well-integrated part of mainstream economics.

The *New Economic Geography* is a body of literature that encompasses tractable models of competition and geographical interdependence in the presence of increasing returns to scale (see Fujita, Krugman, and Venables (1999) for an excellent overview). As a consequence the idea of market potential is now well-incorporated in a solid theoretical framework. In particular, in the models of Krugman (1991) and Helpman (1998) urban agglomeration is associated with persistent spatial wage differentials as the result of increasing returns to scale in production in combination with the existence of transportation costs associated with shipping goods and services from producers to consumers.[3] Within this literature there are also models that, in addition to *output market access,* also consider the importance of *input supply access,* i.e. by assuming that intermediate goods are used in production that have to shipped between producers (e.g. Krugman and Venables, 1995).

A few studies exist that incorporate these models in an empirical framework (Hanson, 2000; Brakman, Garretsen, and Schramm, 2002; Davis and Weinstein, 1999; Redding and Venables, 2003). In particular, the studies of Hanson (2000) and Brakman, Garretsen, and Schramm (2002), which are similar in spirit to this study, use data on U.S. counties and German States, respectively, and obtain results that support the predictions of the Krugman/Helpman model. Their measures of market access have strong effects on regional wages, and within those measures, distance has a highly significant effect. Hanson's (2000) results on U.S. data suggest that prices are marked up 15-25% above marginal cost and Brakman, Garretsen, and Schramm's (2002) results on German data suggest a somewhat higher markup.

However, these findings could partly or fully be explained by other mechanisms, than those stressed by the New Economic Geography models. It has been proposed in the literature that producers in densely populated markets take advantage of positive externalities associated with the local human capital, such as those associated with knowledge spillover (Lucas, 1988; Ciccone and Hall, 1996) or the matching process between workers and firms (Wheeler, 2001). These papers suggest that high-human capital workers sort into urban environments, which has a direct effect on wages in urban areas; and that there are positive externalities associated with the local hu-

[3] The key elements of Krugman's (1991) and Helpman's (1998) model will be further described in Section 3.

man capital. Rauch (1991) presents empirical evidence showing that the wage of a single worker (controlling for the worker's own human capital) is increasing in the average human capital of that worker's location.[4]

The ways this study contributes to the existing literature reflect that it, unlike previous studies, uses micro data to test the empirical validity of a New Economic Geography model. Besides the usual advantages of micro data, such as avoiding the potential effects of aggregation bias, there are several other benefits in this context. For one thing, micro data improve the possibility to separate out any effects on firm-level wages from, on the one hand, market access and, on the other, the direct and indirect effects of spatial sorting of workers with respect to human capital.

Another advantage is related to the fact that by using micro data, certain unrealistic assumptions of the theoretical model can be relaxed. For instance, transportation costs and production parameters that are uniform across firms are convenient assumptions to make in a theoretical framework, but may impose to much structure in an emprical context. In reality some goods and services are very costly to transport (certain kinds of services are even impossible to transport at any cost), whereas other goods and services can be transported at very low costs. Heterogeneity in transportation costs implies that the location decision is more important for firms with high transportation costs. If transportation costs are also correlated with other characteristics of the firm that have an independent impact on earnings, differences in wages across regions cannot be attributed to market potential effects, without actually controlling for those characteristics.

Another key difference between this study and previous ones, which is also related to the use of micro data, is that I analyze the the spatial variation of wages across firms within relatively small areas (individual U.S. states), as opposed to e.g. the variation in wages across counties in the U.S. This means that my estimates reflect the effects of variation in local product demand, rather than the effects of variation in demand across states and countries. Given the amount of unexplained heterogeneity across firms even within narrowly defined sectors of small regions, it is relevant to study what role the variation in local product demand plays to explain firm-level wage heterogeneity. Furthermore, the model that is estimated assumes instantaneous real wage equalization through labor mobility, which is an assumption that is more plausible in small areas than in larger ones.

[4]See also Glaeser and Mare (2001).

2.2 The Relative Importance of the Firm on Pay

Since an important contribution of this paper is the ability to separate the effects on firm-level wages from, on the one hand, market access and, on the other, the direct and indirect effects of spatial sorting of workers with respect to human capital are disentangled, this section will describe in some detail the methodology used to accomplish this.

In seminal work using large scale micro data on firms and workers Abowd, Kramarz, and Margolis (1999) dealt with both the technical and computations difficulties associated with estimating individual and firm fixed effects. Briefly, they exploit the universal and longitudinal nature of the dataset to directly estimate the following regression[5]

$$y_{it} = x_{it}\beta + \theta_i + \psi_{j(i,t)} + \varepsilon_{it} \tag{2}$$

The first, $x_{it}\beta$, is a component based on labor market experience.[6] The second term, θ, is an individual or person effect, which does not vary over time or across employers. The individual effect includes some factors that are often observable to the statistician (such as gender and years of education) and unobservables. The third term, ψ is the firm effect, which measures the markup on wage that is solely attributable to firm-specific factors.[7]

This study relates to this literature by investigating how the firm-wage markups are related to firms' decisions about *where* to produce, and, in particular, if these vary with respect to the market potential in any systematic fashion. Even though this has not been the focus of previous studies, some results from this literature have implications for this study as well.

First of all, firm effects can explain a large fraction of the variation in earnings. For instance, in French data firm characteristics contributed to about 40% of the total earnings variation (Abowd, Kramarz, and Margolis, 1999). In the state of Washington, firm effects accounted for some 50% of earnings variation (Abowd, Finer, and Kramarz, 1999).[8] However, these

[5] The technical derivation of the econometric techniques was initially developed in Abowd, Kramarz, and Margolis (1999) and further refined in Abowd, Creecy, and Kramarz (2002). See also Abowd, Lengermann, and McKinney (2002).

[6] The notation is in matrix form: the actual matrix includes experience as a quartic interacted with gender.

[7] The literatue suggests that firms pay observationally equivalent workers different wages for a variety of reasons ranging from efficiency wage, internal labor market and implicit contract theories to rent sharing and insider/outsider models. See Dickens and Katz (1987) and Groshen (1991) for a good survey of these; more recent discussion include Kremer and Maskin (1996) and Sattinger (1993).

[8] The establishment wage differentials do not disappear when controlling for occupation,

studies do not analyze to what extent the variation of firm markups are related to the location of firms.

Secondly, there is strong evidence of sorting of workers and firms.[9] For instance, of the raw inter-industry and firm-size wage differentials firm effects explain about 50% and 70%, respectively, and person effects are accountable for the balance (Abowd and Kramarz, 2000). Thus, to the extent that there is an element of spatial sorting of firms by industry and/or by size, we need to control for any independent effects on the firm markups they might have.

3 Theory

To develop the intuition behind the market potential function, this section states the key elements of Krugman's (1991) model as presented in Fujita, Krugman, and Venables (1999) and extended by Helpman (1998) together with a few modifications introduced in this study.[10]

The key assumptions of the model are that consumers value variety, there is increasing returns to scale in production, and there are costs associated with shipping goods and services from producers to consumers. The setup implies that firms, all producing a differentiated good or service, have an incentive to locate in areas where product demand is high. To attract workers to these areas, firms have to compensate workers for higher costs of living in these areas. The model is consistent with persistent spatial nominal wage differentials.

3.1 Consumer Behavior

Every consumer shares the same Cobb-Douglas tastes for two types of goods,

$$U = X^{\alpha} H^{1-\alpha} \tag{3}$$

where X is a composite index of the consumption of all goods and services, H is the consumption of housing services (think of this as consumption of

instead high paying firms pay both their lawyers and their janitors a wage premium Lane, Salmon, and Spletzer (2002).

[9] The estimates of the firm and the person effects are the exact OLS solutions. Thus, the identification of these effects are not contigent on assuming that the two effects are orthogonal.

[10] The model of Krugman (1991) builds on earlier work by Henderson (1974), Papageorgiou and Thisse (1985), and Fujita (1988). Like the *New Trade* and the *New Growth* theory, much of the work within the New Economic Geography relies on assumptions of monopolistic competition (Dixit and Stiglitz, 1977) when modeling increasing returns.

all non-tradable goods), and α is a constant representing the expenditure share of traded goods and services.

The index X is a subutility function defined by a constant-elasticity-of-substitution function over a continuum of varieties of goods and services,

$$X = \left[\int_0^n x(i)^\rho di \right]^{1/\rho} \tag{4}$$

$x(i)$ denotes the consumption of each available variety, n is the number of available varieties, and $\rho \in (0,1)$ represents the intensity of the preferences for variety in goods and services.

For a given set of prices and income, the following uncompensated consumer demand functions for each variety of goods and services can be obtained

$$x(j) = \alpha Y \frac{p(i)^{-\sigma}}{G^{-(\sigma-1)}} \text{ for } j \in [0,n], \tag{5}$$

where $G \equiv \left[\int_0^n p(i)^{1-\sigma} di \right]^{1/(1-\sigma)}$ is a price index for goods and services, and $\sigma = 1/(1-\rho)$ is the elasticity of substitution between any two varieties.

The setup implies that an increase in the range of varieties reduces the price index (because consumers value variety) and, hence, the cost of attaining a given level of utility.

3.2 Multiple Locations and Transportation Costs

There is a finite number of locations, denoted with $r = 1, ..., R$. Because of increasing returns to scale and consumers' preferences for variety, each variety of X is produced in exactly one location. To simplify matters, we define regions such that each region contains exactly one firm and, hence, r will be used to index locations as well as varieties of X.

Goods and services can be shipped between locations, but incur transportation costs in shipment in the form of iceberg costs (Samuelson, 1952), such that the c.i.f. price in location s of the good or service produced in location r is $p_{rs} = p_r \exp(d_{rs}\gamma_r)$, where f.o.b. prices in location r are denoted by p_r. The transportation cost parameter is also indexed by r, since transportation costs are allowed to vary across businesses.

This implies that the price index in a particular location can be written as

$$G_s = \left[\sum_{r=1}^{R} (p_r \exp(d_{rs}\gamma_r))^{1-\sigma} \right]^{1/(1-\sigma)} \tag{6}$$

3.3 Producer Behavior

Goods and services are produced with increasing returns to scale, such that the production of quantity q_r of any variety at any given location requires labor input l_r, given by

$$l_r = F_r + c_r q_r \tag{7}$$

Both the fixed cost parameter F_r and the variable cost parameter c_r are indexed by r as they can vary across firms. Profit for a firm is given by

$$\pi_r = p_r q_r - w_r(F_r + c_r q_r) \tag{8}$$

and profit maximization, assuming that each firm taking the price indices, G_s, as given, implies the following pricing rule

$$p_r = c_r w_r / \rho \tag{9}$$

for the single variety produced at r, i.e. prices are marked up over marginal costs by the constant $\sigma/(1-\sigma)$.

By imposing free entry and exit it can be derived that an active firm breaks even if and only if the price it charges satisfies

$$p_r{}^{\sigma} = \frac{c_r \alpha}{F_r(\sigma - 1)} \sum_{s=1}^{R} Y_s \exp(d_{rs}\gamma_r)^{1-\sigma} G_s^{\sigma-1} \tag{10}$$

Using the pricing rule this can be expressed as

$$w_r = \left(\frac{\sigma - 1}{\sigma c_r}\right) \left[\frac{c_r \alpha}{F_r(\sigma - 1)} \sum_{s=1}^{R} Y_s \exp(-d_{rs}\gamma_r)^{\sigma-1} G_s^{\sigma-1}\right]^{1/\sigma} \tag{11}$$

This equation can be thought of as a spatial labor demand function – the demand for labor is higher the closer is a region to areas with high consumer demand. Wages in a location are increasing in the income of surrounding locations, decreasing in transportation costs to these locations, and increasing in the prices of competing traded goods in these locations.[11]

[11] Note that the model contains no explicit spatial linkages through supply access, i.e. via shipment of intermediate goods used in production between producers like in Krugman and Venables (1995). These models rely on the assumption of labor immobility between regions, which is an implausible assumption in the empirical context of many small regions within a small area. For the observation that the two types of model are analytically similar, see Puga (1999).

3.4 Equilibrium

Although no dynamics are explicitly modeled, it is assumed that workers reallocate instantaneously so that real wages are equal across regions. Real wages in region r is given by

$$\omega_r = \omega = w_r (p_r^H)^{\alpha-1} G_r^{-\alpha} \tag{12}$$

Equilibrium in the housing market in each region is characterized by that the payments for housing services (to absent land lords) equal the expenditure share on housing services

$$p_r^H H_r = (1-\alpha) Y_r \tag{13}$$

Finally, the nominal income in each region is simply given by the labor income in that region

$$Y_r = L_r w_r \tag{14}$$

determines income in each region. The equilibrium is jointly determined by (6), (11), (12), (13) and (14).

To develop some intuition behind the agglomeration forces at work in the model consider the effects of an exogenous increase in income in a particular area. In equilibrium with free entry and exit this is consistent with an increase in nominal wages. According to equation (11) this effect is decreasing in the distance to the region immediately affected and the substitution elasticity between any two pair of goods. The increase in nominal wages in a region relative to others triggers a process of worker reallocation to that area. The inflow of workers in a region is also associated with secondary agglomeration effects as the income increases even further by worker inflow (equation (14)).[12] However, the housing market acts as the centrifugal force of the economy, since the increase in the demand for housing services in the region decreases real wages and, thus, counteracts further agglomeration. This effect must dominate any secondary agglomeration effects caused by the inflow of workers, otherwise the region would be a "black hole". For similar reasons, an exogenous increase in the housing stock is associated with agglomeration effects and increases in nominal wages.

[12] In addition there is an upward preasure on real wages, not only because of an increase in nominal wages, but also because the price index (G) decreases. This effect follow since the zero profit condition is satisfied via an increase in the number of varieties produced in the region and since G is decreasing in the number of varieties produced (consumers value variety).

4 Empirical Setup

Instead of estimating the spatial labor demand equation directly, since no good regional price indexes are available, I follow Hanson's (2000) approach and substitute the equilibrium equations (12) and (13) into (11), take logs and append the equation with a statistical residual, ε, to obtain

$$\log w_r = \kappa_r + \sigma^{-1} \log \left[\sum_{s=1}^{R} Y_s^{\frac{\sigma(\alpha-1)+1}{\alpha}} H_s^{\frac{(\sigma-1)(1-\alpha)}{\alpha}} w_s^{\frac{\sigma-1}{\alpha}} e^{-d_{rs}(\sigma-1)\gamma_r} \right] + \varepsilon_r \quad (15)$$

The structural parameters of interest to be estimated are σ, the elasticity of substitution, α, the expenditure share on goods and services, and γ_r, the transportation costs. κ_r is a combination of parameters of production, (thus, it is indexed by r) and preferences. However, before (15) can be implemented in any empirical framework, there are several estimation issues that need to be addressed.

4.1 Estimation Issues

The estimation issues include choosing the unit of geography for the analysis and potential problems associated with the properties of the residual in equation (15).

To test the market potential model, it is important to separate out any human capital effects from the effects of urban agglomeration on pay. Therefore, the wage markup, ψ, as defined by the wage decomposition described in (2) is used as the dependent variable in the model. (Remember that ψ is the estimated firm wage markup net of any observable or unobservable effects of human capital.) Thus, the dependent variable is measured net of any direct effects of spatial sorting of workers with respect to the level of human capital. Firm-level variables are henceforth denoted by j.

Important choices have to be made also with respect to the units and area of analysis. The variable on the left-hand side of (15) can be observed in every location where an active firm exist. The variables on the right-hand side, on the other hand, are defined only in all areas where at least one active firm exists and one individual resides – assuming that consumption takes place where individuals live, rather than work, income is a place of residence concept and wage is a place of work concept. However, further aggregation of the variables on the right-hand side is needed, since the summation in (15) is across the number of areas times four variables for each observation in data. To reduce the dimension of this matrix, the variables on the right-hand side are aggregated to the level of Census Tracts.[13] The distance measure is between the geographical coordinates of the establishment and the corresponding coordinates of the employment-weighted center of the census tract that defines the right-hand side variables. Variables at the Census-Tract level will henceforth be denoted by s.

Even at this level of aggregation, the dimensionality of this matrix is such that the model cannot be estimated across too many regions. Therefore, I restrict the analysis to the state of Illinois, in which there are 2,966 Census Tracts. This implies that the summation for each observation is across 11,864 variables. I also conduct the analysis separately for another state, with somewhat fewer Census Tracts.[14]

By restricting the area of analysis to single states, one potentially important source of omitted variable bias is introduced. This steams from the fact that no state is a closed economy, but instead goods are exported across state borders as well as to other countries. As a result the estimates in here should be viewed as the effects of local demand. Even so, a firm in Illinois, which is located at the border to Indiana is likely to have a higher fraction of its sales to that state than a firm located in the middle of Illinois. To at least partially overcome the effects of truncated spatial distributions of key variables, I interact the summation of income with a set of dummy variables in all specifications, indicating the distance from the establishment and the closest state border.[15]

Because estimation is quite CPU-intensive, I allow only for limited heterogeneity in transportation costs and production parameters. The transportation cost parameter γ is allowed to vary across major SIC divisions and κ, the combination of parameters that include the production parameters, is allowed to vary across major SIC divisions and 6 categories of employment

[13] Census tracts are relatively small geographical units of between 1,500 and 8,000 individuals - averaging about 4,000. While they are not designed to be a local labor market, they are chosen to be relatively homogenous in terms of population characteristics, economic status, and living conditions.

[14] For confidentiality reasons the identity of this state cannot be revealed, but I will discuss the extent to which the results based on Ilinois data differ from the result based on data on this other state.

[15] Establishments are classified according to whether they are located in counties touching the border of the state, counties that touch the border of another county touching the border of the state, and other counties. I have also experimented with other classification schemes, such as the simple measures of the distance to Chicago, based on the argument that the infrastructure in Chicago is used as a hub for national and international trade. The estimates of the parameters of primary interest in are not sensitive to these modifications.

size.[16]

The theoretical model is not intended to explain the factors that initially triggered the process of urban agglomeration, but instead it relates wages to the spatial distributions of various resources in equilibrium. The regressor function includes variables that directly and indirectly via the spatial demand linkages may be correlated with the disturbance term

By measuring the dependent variable at the finest level of aggregation while aggregating the variables in the regressor function to the census tract level, the latter variables should be less influenced by shocks at the establishment level. The measure I use as the dependent variable should also reduce any correlation between the error term and the regressor function. To further minimize potential problems related to endogenous right-hand side variables, income is measured as the sum of labor income in the region except for the income that is generated from the establishment for which the dependent variable is defined.

In addition results for two samples of firms are reported: all establishments and establishments with less than 50 employees.[17] Shocks to large establishments may influence economic activities in other regions, while shocks to small establishments are less likely to do so. If coefficient estimates are similar in the two samples of firms, then it would appear that the endogeneity of the independent variables does not have serious consequences for the estimation results.

Taking the considerations above into account I estimate versions of the following equation:

$$\psi_j = \kappa_{x(j)} + \sigma^{-1} \log \left[\sum_{s=1}^{R} (1+\delta z_j) \widetilde{Y}_s^{\frac{\sigma(\alpha-1)+1}{\alpha}} H_s^{\frac{(\sigma-1)(1-\alpha)}{\alpha}} \widetilde{w}_s^{\frac{\sigma-1}{\alpha}} e^{-\widetilde{d}_{js}(\sigma-1)\gamma_{x(j)}} \right] + \varepsilon_j \tag{16}$$

where ψ_j is the estimated wage markup at establishment j (defined in logs); $x(j)$ is a function that assigns establishments to the major SIC division and employment size category it belongs to; z_j is a set of dummies indicating the distance from the establishment to the closest state border; $\widetilde{Y}_s$ is the sum of labor income in census tract s, net of the possible contribution from employees in establishment j; H_s is measured as the number of housing units in census tract s; $\widetilde{w}_s$ is the mean of wages of all workers who live in

[16] The Agriculture and the Mining major sectors are collapsed into one industry. The size categories are: 1-10, 11-25, 50-100, 100-250, 250-500, 500-∞.

[17] Hanson (2000) uses a similar approach when reporting results for all and small counties only.

census tract s, net of possible contributions from worker who are employed by establishment j; and $\widetilde{d}_{rs}$, finally, is the straight-line distance in miles between the geographical coordinates of establishment j and the coordinates of the employment-weighted center of census tract s.[18]

Finally, to address the potential problem of inference in the presence of correlation between the variance of disturbanc term and the regressors, I follow Brakman, Garretsen, and Schramm (2002) in applying a Glesjer test (Glesjer, 1969). In particular, I first estimate the non-linear least squares residuals from equation (16) (and any other specification presented) and subsequently use the absolute value of these as the dependent variable in a regression on the variables in the regressor function in equation (16). A significant impact of the these variables indicates the presence of heteroscedasticity. Indeed, in each of the specifications estimated, the null hypothesis of homoscedasticity of a Wald test is rejected. Therefore I present weighted non-linear least squares estimates, where the weights are taken from the estimation results from in the first step.

5 Data

The U.S. Census Bureau's Longitudinal Employer-Household Dynamics Program (LEHD) has developed a unique database, which can be used to describe the interactions between workers and firms over space and time. This new database enables us to match workers with past and present employers, together with employer and worker characteristics. This database consists of quarterly establishment records of the employment and earnings of almost the universe of workers and firms in the participating states.

These type of data are extensively described elsewhere (Haltiwanger, Lane, and Spletzer, 2000; LEHD, 2002), but it is worth noting that there are several advantages over household based, survey data. In particular, the earnings are quite accurately reported: there are financial penalties for misreporting. The data are current, and the dataset is extremely large. Since we have almost the full universe of employers and workers, we can track movements across earnings categories and across employers with a great deal of accuracy. The Unemployment Insurance records have also been matched to internal administrative records that have information on date of birth, place of birth, race and sex for all workers. In addition, we

[18] For comparision, Hanson (2000) defines the left-hand side variable at the county level, the right-hand side variable at the level of states, excludes own-county level from the summation on the right-hand side, and takes first differences of the equation.

have place of residence for almost all workers in the most recent years, and the location of all businesses for all quarters for which we have data.

There are some disadvantages as well. These job-based data are different from the worker based data with which many researchers are familiar. Earnings refer to quarterly earnings, we have no information on either wage rates or hours and weeks worked, and only limited demographic information about workers is available.[19]

This study uses data for the state of Illinois and another undisclosed state. The universe is defined by all active establishments in 1999. In Illinois this amounts to approximately 330,000 establishments and together these businesses employ about 5,800,000 workers. Establishments and workers have been geocoded on a latitude and longitude basis using internal Census mapping software. The quality of the geocoding is quite good. Approximately 97% of all workers and establishments have geocodes that uniquely define the relevant census tract level or better (in this group, all but a few percent are geocoded to the roof top). Individuals and establishments that cannot geocoded at least to the census tract level have been dropped from the analysis. Currently only residence data for 1999 are available and, thus, all results presented reflect that year.

These data have been integrated with person and firm fixed effects estimates from the LEHD Employment Dynamics Estimates database. In the case of Illinois the person and firm effects have been identified using over 57 million annual observations from 1990 to 2000 for over 11.2 million workers and 462,000 firms.

In addition, information on the number of housing units in the Census Tracts have been collected from public use Census data.

6 Descriptive Results

In this section I present graphical evidence of urban agglomeration effects on pay and spatial sorting of workers and firms, using ARC-GIS mapping techniques. The variables of interest used in the graph below are derived from earnings decomposition in (2) and, therefore, I first summarize the results from this decomposition.

[19] The linking possibilites to survey data such as CPS, SIPP and the Decennial Census mean that rich demographic information is available for a subset of all workers. In the estimation of (2) statistical matching techniques have been used to control for full- and part-time status.

Table 1: Summary of estimated wage components in Illinois

Component	Standard deviation	Correlation with y	θ	ψ	$x\beta$	ε
Log real annual wage rate (y)	0.874	1.000	0.532	0.473	0.254	0.407
Person effect (θ)	0.757	0.532	1.000	-0.015	0.500	0.000
Firm effect (ψ)	0.383	0.473	-0.015	1.000	0.074	0.000
Time-varying personal characteristics ($x\beta$)	0.572	0.254	0.500	0.074	1.000	0.000
Residual (ε)	0.356	0.407	0.000	0.000	0.000	1.000

Based on 57,101,720 annual observations from 1990 to 1999 for 11,207,030 persons and 462,577 firms in the state of Illinois. Source: LEHD Program Employment Dynamics Estimates database.

6.1 Earnings Decomposition

Table 1 shows the correlation between different wage components in Illinois over the period 1990 to 2000. The first thing to note is the explanatory power of this decomposition. The correlation between the residual and the wage measure is 0.407, which translates into an R-square of about 85%.

The second thing to note is the importance of firm effects. The simple pairwise correlation of the estimated firm effect and earnings is 0.47. This number is substantially higher than the correlation between the effects of observable personal characteristics and earnings and just slightly lower than the correlation between the effects of unobservable person characteristics and earnings.

The third thing to note is that at an individual level, worker and firm effects are essentially uncorrelated. As will become obvious in the next section, this is no longer true once the effects are aggregated by location.

6.2 Graphical Evidence of Urban Agglomeration Effects and Sorting of Workers

As a point of departure, the map in Figure 1 shows the population density across Census Tracts in Illinois.[20] The map also shows cities with a population larger than 75,000 (according to the Decennial Census 2000) and the cities of Urbana-Champaign (the home of University of Illinois), Normal (the home of Illinois state University), Macomb (the home of Western Illinois University) and East St. Louis, which is an area in South West of

[20] To guarantee confidentiality in data, all values depicted in the maps are based on at least 5 observations. If there are fewer than that number of observations, values are smoothed across adjacent tracts.

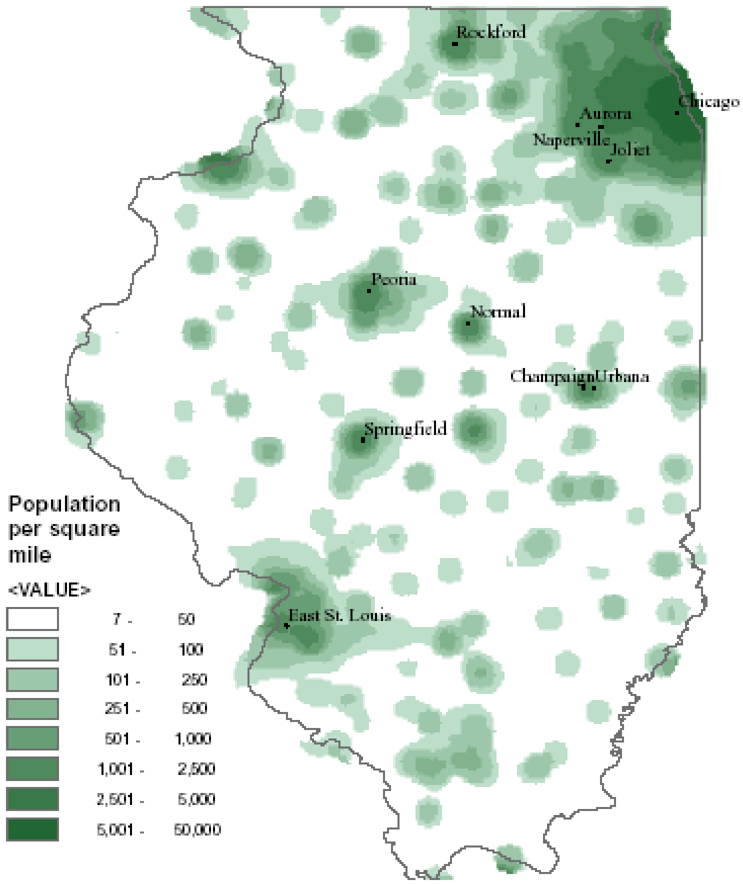

Figure 1: Population censity in Illinois in 2000

Illinois where the population density is relatively high. The population concentration is such that half the population is concentrated to Census Tracts accounting for little more than 1% of the total land area of Illinois. The least populated areas in Illinois, accounting for 50% of the land area, are the homes for only 4% of the population.

Figure 2 shows the employment density (as of 1999) across Census Tracts in Illinois. By comparing the two maps we note that employment is even more concentrated than is the population. The employment concentration is such that half the workforce work in Census Tracts accounting for less than 1% of the total land area. Similarly, the least economically active Census

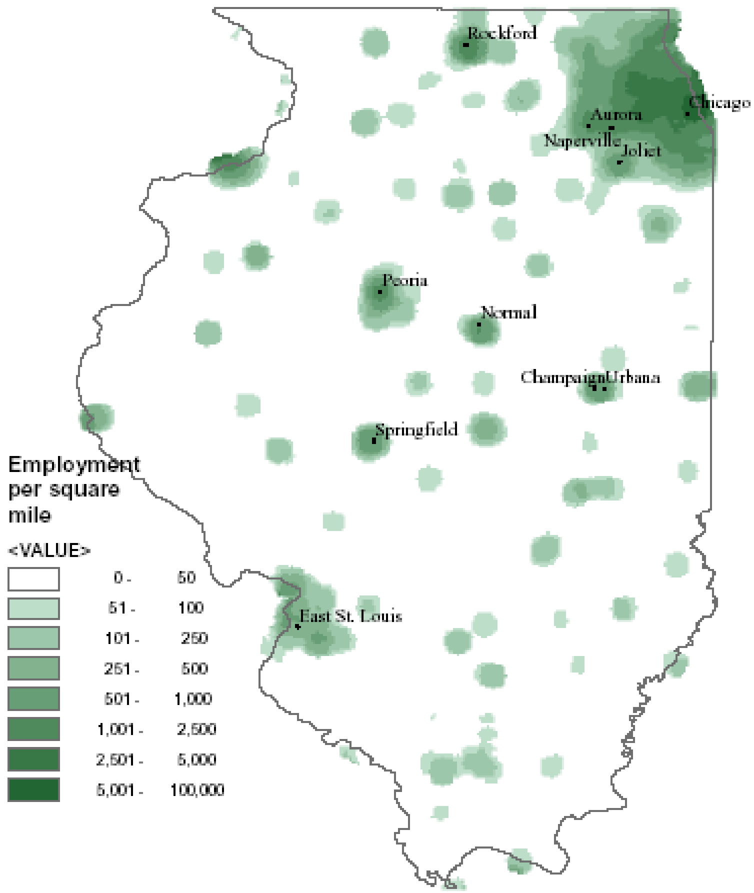

Figure 2: Employment density in Illinois

Tracts, accounting for 50% of the land area, employ only 1% of the workforce. Note that these concentration rates do not measure additional concentration within Census Tracts.

Figure 3 shows the spatial distribution of estimated human capital in Illinois. The measure of human capital is the median of the person effect (θ) from equation (2).[21] By referencing the results in Figure 1 and Figure 2, we see that there is a remarkable correspondence between population density and the median human capital of workers by their place of residence. Apart from this general result, a couple of other interesting findings are worth pointing out: The horse-shoe shaped area of high levels of human capital around Chicago are areas from which affluent workers commute to jobs in and around Chicago. The area South-East of Chicago, where the level of human capital is lower, is an area which is heavily industrialized and polluted. Also note the high levels of human capital in the university areas and south of Springfield, the capital of Illinois. This map suggests that at least part of the explanation of why wages are higher in urban areas is because workers living in those areas have higher than average levels of human capital.

Figure 4 maps the distribution of median firm wage premia across the Census Tracts in Illinois. Again, there is a strong correspondence between population density and median firm wage premium in the areas, suggesting that there is an effect on firm-wages of market access, independent of human capital differences. However, part of this result could be driven by differences in the industry structure between urban and more rural areas. Figure 5 maps the spatial distribution of firm wage premia net of industry effects.[22] The results suggest that the spatial differences in industry structure works in favor of equalizing spatial differences in median firm-wage premia, rather than the opposite. Thus, these maps strongly indicates that there are urban agglomeration effects on wages, independent of any human capital or industry effects. Table 2 confirms most of these finding by showing the simple correlation between medians of wage components and measures of population and employment densities across Census Tracts.

Table 3 and Table 4 present the distributions of employment and firm-

[21] Whether in addition the experience component ($x\beta$) from the wage decomposition is included does not make a difference for the qualitative results. When aggregating person and firm effects to the level of census tracts I chose to use medians to avoid the influence of extreme values. However, none of the qualitative results reported in this study change if I instead use means.

[22] The industry effects are calculated as the employment weighted mean of all firm-wage premia within each major group (2-digit SIC).

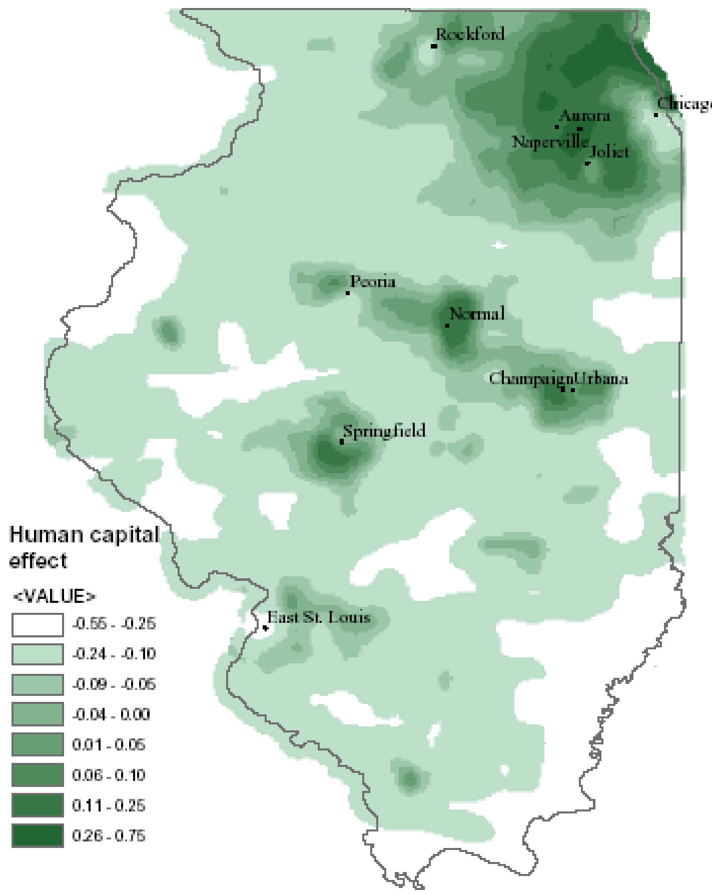

Figure 3: Distribution of median human capital in Illinois

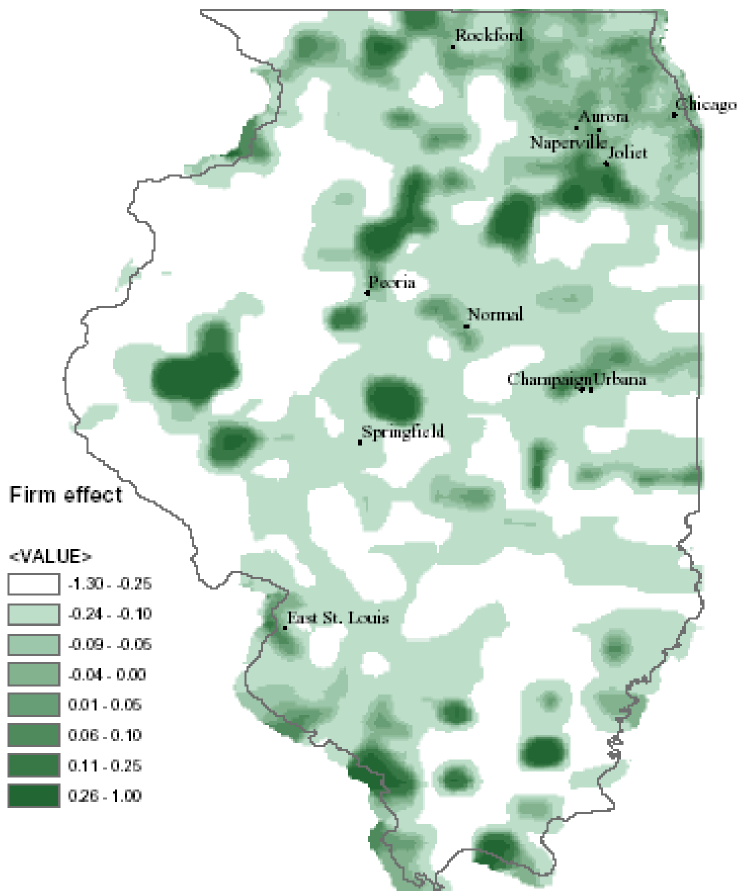

Figure 4: Distribution of median firm effects in Illinois

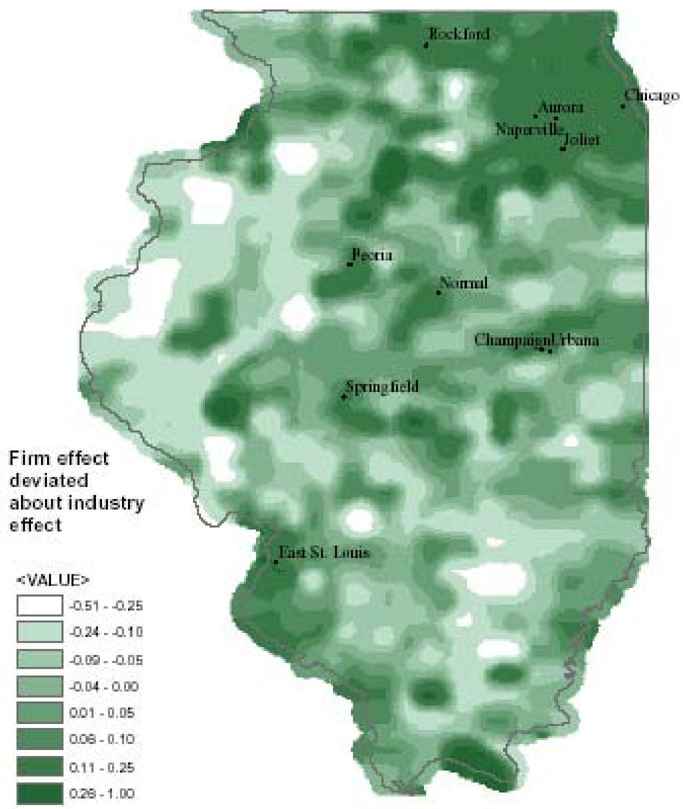

Figure 5: Distribution of median of firm effect deviated about industry effect in Illinois

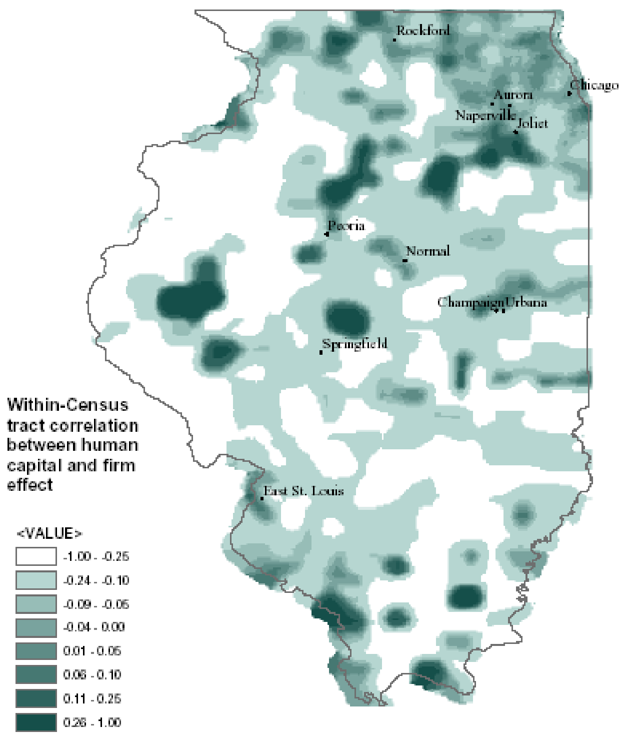

Figure 6: Distribution of within-Census Tract correlation between human capital and firm effects

Table 2: Correlation of wage components across Census Tracts

Median of	Standard deviation	Correlation with y	θ	ψ	$\psi - \psi^{ind}$	pop	emp	$corr(\theta, \psi)$
y	0.309	1.000	0.901	0.121	0.183	0.121	0.214	0.161
θ	0.222	0.901	1.000	0.094	0.171	0.187	0.281	0.179
ψ	0.210	0.121	0.094	1.000	0.863	0160	0.341	0.137
$\psi - \psi^{ind}$	0.179	0.183	0.171	0.863	1.000	0.239	0.376	0.171
pop	2.107	0.121	0.187	0.160	0.239	1.000	0.818	0.226
emp	2.361	0.214	0.281	0.341	0.376	0.818	1.000	0.214
$corr(\theta, \psi)$	0.087	0.161	0.179	0.137	0.171	0.226	0.214	1.000

The correlations are calculated across medians in 2,966 census tracts in Illinois. $\psi - \psi^{ind}$ is the firm effect deviated about the industry effect, *pop* is population per square mile, *emp* is employment per square mile and $corr(\theta, \psi)$ is the within-Census Tract correlation between θ and ψ. All correlations are statistically significantly different from zero at the the one-percent level.

wage premia across categories of Census Tract population density by major SIC divisions. Table 3 shows that the industry structure varies with respect to the population density in expected ways. Table 4 shows that there is a strong relationship between population density and firm-wage premia in most industries. For instance, in the Service sector there is a 23 log points difference in the mean wage premium for establishments located in Census Tracts with more than 5,000 residents per square mile compared to the establishments located in Census Tracts with fewer than 250 residents per square mile. There are exceptions as well: more urban establishments within Agriculture & Mining do not pay a higher wage premium than their more rural counterparts.[23]

Are these results consistent with the idea of increasing returns to scale in firms' production technology together with transportation costs as the driving force of urban agglomeration? That the wage mark-ups of firms, which are net of any direct effects of sorting of high human capital workers into urban areas, are highly correlated with population density is consistent with this idea, but these patterns are certainly not exclusive evidence in favor of the increasing returns explanation.

For instance, the model of Wheeler (2001) in which the urban agglomera-

[23] The level of aggregation might conceal that such a relationship exists after all. Urban establishments within this group of industries consist mainly of establishments within the Agricultural Service industries.

Table 3: Distribution of employment across population density cateogories by major SIC divisions

Population/square mile Major SIC division	[0,100)	[100,1000)	[1000,5000)	[5000,∞)	All
All	8.83	16.71	45.20	29.26	100.00
Agriculture & Mining	24.41	25.83	36.37	13.38	100.00
Construction	16.19	22.51	41.47	19.82	100.00
Manufacturing	7.90	19.02	47.86	25.23	100.00
TCU	17.31	20.81	40.29	21.60	100.00
Wholesale Trade	8.94	16.42	51.92	22.71	100.00
Retail Trade	7.79	17.32	42.58	32.31	100.00
FIRE	5.96	13.65	45.59	34.80	100.00
Services	5.29	13.98	47.13	33.60	100.00
Public Admin.	45.74	23.14	24.50	6.63	100.00

Table 4: Distribution of employment-weighted firm wage premia across population density cateogories by major SIC divisions

Population/square mile Major SIC division	[0,100)	[100,1000)	[1000,5000)	[5000,∞)	All
All	-0.12	-0.04	0.01	0.03	0.00
Agriculture & Mining	0.09	-0.11	-0.07	-0.14	-0.04
Construction	-0.07	0.16	0.21	0.22	0.18
Manufacturing	0.13	0.21	0.23	0.20	0.22
TCU	0.10	0.15	0.17	0.29	0.16
Wholesale Trade	-0.07	0.08	0.18	0.17	0.15
Retail Trade	-0.35	-0.31	-0.32	-0.31	-0.32
FIRE	-0.21	0.08	0.18	0.28	0.20
Services	-0.24	-0.13	-0.06	0.01	-0.05
Public Admin.	-1.02	-0.43	0.16	-0.02	0.04

tion effects are attributable to externalities in the matching process between workers and firms could generate similar patterns. The key assumptions of this model are skill-capital complementarity and lower search costs in an urban than in a rural environments. This setup results in higher average firm wage markups in cities and sorting of high-skill workers into cities. In addition, the model predicts more segregated matches in urban environments. Does this latter prediction have support in our data? Remember that Table 1 showed that person and firm effects are virtually uncorrelated at the individual level. Figure 6 depicts the spatial distribution of this correlation across Census Tracts. Consistent with Wheeler's model the correlations between person and firm effects tend to be more positive in densely populated areas than in rural areas. In addition there are other explanations based on externalities in the human-capital mentioned in the introduction that could at least contribute to explain this findings.

In summary, the descriptive results are consistent with increasing returns to scale in the firms' production technology as a driving force of urban agglomeration, but the patterns presented in this section could partly or fully be explained by other hypotheses as well.

In comparison, the results for the other state for which the analysis has been undertaken are for most parts qualitatively the same. The one difference is that the spatial differences in industry structure in the other state increase, rather than decrease, spatial differences in firm's pay.

7 Regression Results

In this section I report the results from the estimation of the model presented earlier. I discuss what the implications of these results are for urban agglomeration. I then explore the quantitative significance of our results for explaining differences in wage markups across businesses. As a first test of the importance of market potential function, however, I estimate a simplified version, which imposes less structure and is close in spirit to the simple market potential function in (1). A summary of the variables used in the regression analysis is provided in Table 3. All regressions are based on a 10% sample of establishments in 1999 with sample weights proportional to employment. To increase the spatial variability in data a somewhat higher fraction of establishments were sampled outside the Chicago area.

Table 5: Summary of regression variables

Variable	Mean	Std. dev.
ψ	0.000	0.299
Y	3,028	2,891
w	1.283	0.250
H	1,647	914

See text for definitions of variables.

7.1 The Simple Market Potential Function

The first model I estimate relates the firm wage markup to the spatial distribution of income weighted by distance:

$$\psi_j = \alpha + \beta \log(\sum_{s=1}^{R} \widetilde{Y}_s \exp\{-\gamma_1 \widetilde{d}_{js}\}) + \varepsilon_j \tag{17}$$

where the dependent variable and the variables in the regression function are defined as in (15), and α, β and γ are the parameters of primary interest to be estimated.

The nonlinear weighted least squares estimates are reported in Table 6. Column (i) reports the results on the full sample without industry and size controls. All coefficients are precisely estimated. The coefficient β measures the effect of the market potential index on the establishment wage markup. Consistent with the market potential hypothesis, the point estimate is positive. Within the market potential index, the coefficient γ measures the effect of distance on the wage markup. Also consistent with the market-access hypothesis, the coefficient is positive (meaning that income far away from the establishment influence the wage markup less than income in the proximity of the establishment's location).

Column (iii) show that the results are very similar when the model is extended to allow for industry- and size-class specific intercepts. The unreported parameter estimates are as expected, i.e. there is a significant establishment size premium and the industry wage premia correspond well to the differences in mean firm wage premia across industries in Table 4.

Column (v) reports the results, when in addition, the distance parameter is allowed to vary across major SIC divisions. This increases the importance of the market potential index and an F-test that the γ parameters are the

Table 6: Market potential function estimates

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
β_1(Market Potential)	0.042	0.037	0.038	0.036	0.070	0.065
	(0.003)**	(0.003)**	(0.003)**	(0.003)**	(0.009)**	(0.005)**
γ_1(Distance)	0.183	0.221	0.206	0.231		
	(0.037)**	(0.053)**	(0.038)**	(0.053)**		
$\gamma_{\text{Agriculture \& Mining}}$					0.006	0.002
$\gamma_{\text{Construction}}$					0.095**	0.110**
$\gamma_{\text{Manufacturing}}$					0.163**	0.116**
γ_{TCU}					0.049**	0.013**
$\gamma_{\text{Wholesale Trade}}$					0.203**	0.209**
$\gamma_{\text{Retail Trade}}$					0.284**	0.275**
γ_{Services}					0.334**	0.387**
γ_{FIRE}					0.222**	0.214**
$\gamma_{\text{Public Administration}}$					0.425**	0.510**
Additional Controls	No	No	Yes	Yes	Yes	Yes
Sample	All	Small	All	Small	All	Small
Observations	32,800	10,740	32,800	10,740	32,800	10,740
R-squared	0.09	0.08	0.28	0.26	0.31	0.28

Parameters are estimated by weighted nonlinear least squares. The estimated specification is that in (17). All specifications include controls for distance to border county; (i) and (ii) include a constant; and (iii)-(vi) include industry- and establishment size cateogory-specific intercepts. Standard errors are reported within parantheses (to save space, the standard errors associated with the parameters for the heterogenous transportation costs are surpressed). *significant at 5% **significant at 1%

Table 7: Market potential function estimates

	(i)	(ii)	(iii)	(iv)
β_1(Market Potential)		0.042	0.039	0.066
		(0.003)**	(0.003)**	(0.006)**
γ_1(Distance)		0.193	0.208	
		(0.039)**	(0.039)**	
β_2(Human Capital)	0.080	-0.002	0.001	0.003
	(0.010)**	(0.012)	(0.013)	(0.012)
γ_2(Distance)	0.030	0.076	0.045	0.053
	(0.005)**	(0.042)	(0.057)	(0.062)
$\gamma_{\text{Agriculture \& Mining}}$				-0.002
$\gamma_{\text{Construction}}$				0.093**
$\gamma_{\text{Manufacturing}}$				0.161**
γ_{TCU}				0.050**
$\gamma_{\text{Wholesale Trade}}$				0.199**
$\gamma_{\text{Retail Trade}}$				0.283**
γ_{Services}				0.334**
γ_{FIRE}				0.221**
$\gamma_{\text{Public Administration}}$				0.421**
Additional Controls	No	No	Yes	Yes
Observations	32,800	32,800	32,800	32,800
R-squared	0.06	0.10	0.29	0.32

Parameters are estimated by weighted nonlinear least squares. The estimated specification is that in (18). All specifications include controls for distance to border county; (i) and (ii) include a constant; and (iii)-(iv) include industry- and establishment size cateogory-specific intercepts. Standard errors are reported within parantheses (to save space, the standard errors associated with the parameters for the heterogenous transportation costs are surpressed). *significant at 5 % **significant at 1%

same is strongly rejected at all conventional levels of significance. It is natural to intrepret the distance coefficients as measures of transportation costs - this is indeed the interpetation in the Krugman-Helpman model. (We will return to the ordering of transportation costs in the next section.)

Columns (ii), (iv) and (vi) report the results from estimating the specifications in column (i), (iii) and (v) on the sample of establishments with less than 50 employees. Coefficient estimates based on the sample of small establishments are quite similar to the estimates based on the full sample, which suggests that the exclusion of large establishments, for which it seems most likely that the disturbance term will be correlated with the regressor function, does not influence the results.[24]

In Table 7 I add controls for the spatial distribution of human capital weighted by distance to test the hypothesis that firms pay higher wages in regions where the average human capital is high, because of potential externalities associated with the local level of human capital (e.g. Lucas, 1988; Ciccone and Hall, 1996; Wheeler, 2001). Thus, I estimate versions of the following equation

$$\psi_j = \beta_o + \beta_1 \log(\sum_{s=1}^{R} \widetilde{Y}_s \exp\{-\gamma_1 \widetilde{d}_{js}\}) + \beta_2(\sum_{s=1}^{R} \widetilde{\theta}_s \exp\{-\gamma_2 \widetilde{d}_{js}\}) + \varepsilon_j \quad (18)$$

where $\widetilde{\theta}_s$ is the average person fixed effect of workers living in Census Tract s.

Column (i) includes only controls for the spatial distribution of human capital, and consistent with the hypothesis the firm-wage premium is higher where the average level of human capital in surrounding areas is high. However, the results in column (ii) suggest that the effects of the local human capital on firms' wages are the result of its effect on income and not the result of any externalities. That is, once controls for the spatial distribution of income are included, there are no significant effects of the spatial distribution of human capital. Column (iii) adds controls for industry and establishment size and Column (iv), in addition, allows for heterogeneity w.r.t. transportation costs across industries. The results with respect to the importance of the local human capital do not change. The corresponding results based on the sample of small establishments (not reported) are very similar.

[24] Unreported results exluding establishements with more than 25 employees are similar to those in column (iii) of Table 6.

7.2 The Krugman Model

The difference between the market potential function estimated in the previous section and the Krugman model is that the latter incorporates real-wage equalization across regions and equilibrium in the market for space.

Parameter Estimates

The nonlinear least squares estimates of the parameters in (16) are reported in Table 8. Column (i) reports the results with no industry and size-class controls, Column (iii) adds industry-specific and size-class specific intercepts and Column (v) allows for heterogenous transportation costs across industries. Columns (ii), (iv) and (vi) report the corresponding results based on the sample of small establishments. Again, the coefficient estimates in columns (i), (iii) and (v) are very similar to the estimates in columns (ii), (iv) and (vi), respectively. In addition, all specifications have been estimated with the additional additive control for the spatial distribution of human capital, but in all specifications the effect of human capital is insignificant and other parameters virtually unchanged.[25]

As predicted by the theoretical model the point estimates of α, the expenditure share on all traded goods and services, σ, the elasticity of substitution between any two varieties, and γ, the cost of transportation, are all positive. The estimated values for α of 0.73-0.86 are consistent with an expenditure share on housing in the U.S. of about 0.2. However, not all expenditures on housing are related to non-traded goods and services, and not all other expenditures are on traded goods.

As the results in (v) show, data do not support homogenous transportation costs across industries. The point estimates suggest that transportation costs are highest in Public Administration; followed by high transportation costs in Services, FIRE, Retail, and Wholesale Trade; and relatively low transportation costs in Transportation and Utilities, Manufacturing, Construction and Agriculture and Mining.

Does the ordering of transportation costs across industries conform with any *a priory* expectations? The overall pattern seems reasonable, although it is difficult to make any conclusive statements, especially since the level

[25] The model has also been estimated without the theoretical structure imposed on the exponents to the variables. The results are such that the estimated exponents are similar, but not quite the same, to the ones implied in the reported results. I do not report these results, because the unrestricted model is overidentified in the sense that there is no single solution for the structural parameters of the model.

Table 8: Parameter estimates

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
α	0.733	0.857	0.808	0.823	0.823	0.827
	(0.045)**	(0.057)**	(0.005)**	(0.002)**	(0.041)**	(0.051)**
σ	7.767	7.781	10.791	9.942	9.894	11.598
	(0.788)**	(1.273)**	(1.080)**	(1.057)**	(0.904)**	(1.852)**
γ	0.028	0.036	0.027	0.029		
	(0.004)**	(0.005)**	(0.004)**	(0.004)**		
$\gamma_{\text{Agriculture \& Mining}}$					0.003*	0.001
$\gamma_{\text{Construction}}$					0.011**	0.011**
$\gamma_{\text{Manufacturing}}$					0.018**	0.012**
$\gamma_{\text{Transportation \& Utilities}}$					0.018**	0.014**
$\gamma_{\text{Wholesale Trade}}$					0.029**	0.024**
$\gamma_{\text{Retail Trade}}$					0.031**	0.030**
γ_{Services}					0.038**	0.036**
γ_{FIRE}					0.029**	0.031**
$\gamma_{\text{Public Administration}}$					0.045**	0.050**
Additional controls	No	No	Yes	Yes	Yes	Yes
Sample	All	Small	All	Small	All	Small
R-sq.	0.10	0.09	0.31	0.31	0.34	0.33
# Obs.	32,800	10,740	32,800	10,740	32,800	10,740

Parameters are estimated by weighted nonlinear least squares. The estimated specification is that in (16). All specifications include controls for distance to state border; (i) and (ii) include an intercept; and (iii)-(vi) include industry-specific and establishment size-specific intercepts. Standard errors are reported within parantheses (to save space, the standard errors associated with the paramters for the heterogenous transportation costs are surpessed). *significant at 5% **significant at 1%

of industry aggregation is such that a great deal of within-industry heterogeneity in transportation costs is likely to remain. Still, it seems reasonable that the Service, FIRE, and the trade industries have relatively high estimated transportation costs, given the presumably high dependence of local demand in these industries; and Manufacturing relatively low, for the opposite reasons. Even though Construction is an industry that does not produce goods and services that are traded in the traditional sense, the low estimated transportation costs could potentially be explained by that the production *per se* is mobile. The high estimated transportation costs in Public Administration is harder to explain, but may be related to location decisions being driven by other motives than profit maximization.

It is interesting to note that the ordering of transportation costs across industries corresponds quite well with the sorting of industries across population density categories in Table 3, in the sense that high transportation cost industries are more concentrated in high population density areas, with the exception of Public Administration.

In comparison, the results for the other state for which the analysis has been undertaken are similar. With respect to the ordering of transportation costs, Services have relatively lower (but still high) transportation costs and Transportation & Utilities relatively higher in the other state.

Implied Agglomeration Effects

According to the theoretical model $\sigma/(\sigma-1)$ equals the ratio of average to marginal costs in equilibrium and, thus, if this ratio is greater than 1 then the production technology is subject to increasing returns to scale. Table 9 reports estimates of this ratio based on the estimation results in Table 8. The estimated values for this ratio of 1.09 to 1.15, which in all cases are statistically different from 1, are somewhat lower than the corresponding estimates obtained by Hanson (2000) and Brakman, Garretsen, and Schramm (2002).[26] The point estimates of the degree of increasing returns to scale decrease when additional controls for firm heterogeneity are included, suggesting that failing to control for firm heterogeneity could explain the somewht higher estimates in the other studies. On the other hand, the fact that I estimate the effects of variation in local demand could also explain why the estimates presented here are lower.

Increasing returns to scale is a necessary, but not sufficient condition

[26] The estimates of this ratio based on data for the other state are similar. Hanson's estimates range between 1.15 to 1.25 and Brakman, Garretsen and Schrammm's are somewhat higher.

Table 9: Urban agglomeration effects

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$\sigma/(\sigma-1)$	1.148	1.147	1.102	1.112	1.112	1.094
	(0.017)**	(0.012)**	(0.009)**	(0.011)**	(0.009)**	0.014)**
$\sigma(1-\alpha)$	2.073	1.685	1.756	1.751	1.751	2.001
	(0.386)**	(0.695)	(0.582)	(0.455)*	(0.422)*	(0.465)*

Standard errors reported within parantheses. * and ** indicates that the estimate is significant different from 1 at 5% and 1%, respectively

Table 10: Distribution of predicted wage markups associated with spatial factors

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
p25	-0.096	-0.098	-0.112	-0.114	-0.135	-0.136
p50	0.002	0.001	0.003	0.003	0.001	0.000
p75	0.087	0.082	0.089	0.088	0.101	0.098
Std. dev	0.094	0.092	0.096	0.095	0.126	0.125

for urban agglomeration. If $\sigma(1-\alpha) < 1$, then the higher γ is the more geographically concentrated will production be. Alternatively, the degree of urban agglomeration is invariant to transportation costs and depends only on the spatial allocation of housing services. The point estimates of $\sigma(1-\alpha)$, although they are not significantly different from 1 in all cases range between 1.69 to 2.07.

Quantitative Effects

How important are these results quantitatively? Table 10 shows the distribution of the predicted wage markups based only on the spatial factors in the various specifications. The inter-quartile range in the different specification suggests that, because of spatial differences in market access, firms in the bottom quartile pay about 20% lower wages than firms in the top quartile. These are very large numbers that are in same order of magnitude as the fraction of variation in pay that can be explained by industry effects.

Another way to get at the quantitative importance of these results is to simulate a shock to income in one area and look at the effects on wage markups in surrounding areas. The shock I simulate is a 10% decrease in income in the Chicago area. Note that this exercise does not take into account the equilibrium effects and should only be viewed as simulating the short-run outcome. For establishments in Manufacturing located 20 miles away from the area directly affected, the results of this shock is a 4% decrease in the wage markup. Similarly, for an establishments in FIRE located equally far away from the area directly affected, the results of this shock is less than a 1% decrease in the wage markup. For all establishments located 50 miles or further away from the area of impact, the effects on the wage markups are more or less negligible.

8 Summary and Conclusions

In this paper I investigate why wages are higher in urban environments than in rural and what the role of local market access is. When I estimate the parameters of Krugman's (1991) model as extended by Helpman (1998) on micro data taking advantage of variation in local demand, I obtain results that are consistent with the idea that the structure of the spatial wage distribution and urban agglomeration are at least partly the result of increasing returns to scale in production together with the existence of transportation costs. I find that spatial factors can account for a relatively large fraction of the variation in wage markups across firms. Interpreted literally the estimates suggest that average prices are about 10-15% higher than marginal costs.

Furthermore, I show in this paper that the transportation costs are heterogenous across industries and it seems that firms are spatially sorted with respect to transportation costs.

By using micro data the effects on the spatial wage distribution from, on the one hand market access, and, on the other hand, human captial effects can be disentangled. Even though there is a strong relationship between the average level of human capital in a region and wages, the results suggest that the structure of the spatial wage distribution is such, that the firm-level wages net of the direct effects from human capital are mainly determined by market access, rather than any externalities associated with simple controls for the local level of human capital.

Even so, the results do not necessarily rule out alternative explanations for the structure of the spatial wage distribution, including some related to the spatial structure of human capital. For instance, commuting and worker mobility as well as the effects of input-output relationships in firms' production technologies are phenomena that could play an important role in the context of within-state variation in the wage distribution.

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Essay IV

The Interaction of Workers and Firms in the Low-Wage Labor Market

The Interaction of Workers and Firms in the Low-Wage Labor Market*

1 Introduction

As welfare reform was implemented throughout the U.S. in the late 1990's, millions of low-wage female workers entered the labor market. Concerns have been raised not only about their ability to find employment, but also about the levels of wages and benefits that they earn and their potential for earnings growth over time (e.g Committee for Economic Development, 2000; Strawn, Greenberg, and Savner, 2001). Indeed, these factors will be critical determinants of the extent to which low-wage women will be able to escape poverty and achieve economic self-sufficiency for themselves and

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their families. And these issues are clearly just as relevant to low-wage male workers as to their female counterparts.

Yet some very fundamental questions remain about workers in low-wage labor markets in the 1990's and beyond. Among these questions are the following:

- To what extent do low-wage workers experience enough earnings growth over time to "escape" their low-wage or poverty status?

- Do the processes by which workers escape low-wage status differ across demographic groups – especially by gender and race?

- How important is wage growth *within* jobs, as opposed to mobility *across* jobs and employers, for those who escape low-wage status?

- What characteristics of *employers* contribute the most to success in the low-wage market, and which workers are matched to these employers? How important is the quality of that *match* for achieving success in the low-wage market, as opposed to individual skills and other attributes?

These issues are critical to the development of effective welfare-to-work policies, as well as policies for other low-wage workers (as funded by the Workforce Investment Act or more broadly). For instance, they are critical for understanding the extent to which job search and job placement strategies can be successful in helping low-wage workers escape poverty, or the extent to which placement or even training efforts should be targeted towards specific sectors and the skills that are relevant there.

Yet, despite the fairly fundamental nature of these questions, relatively little is known about these issues. The effect of turnover on wage growth has been studied using data from the National Longitudinal Survey of Youth (NLSY79) – such as those by Royalty (1998), Holzer and Lalonde (2000), and Gladden and Taber (2000). These studies clearly indicate the fairly positive effects of voluntary (or job-to-job) turnover on wage growth, and the more negative effects of involuntary (or job-to-nonemployment) turnover.[1] The returns to work experience for low-wage workers have also been documented in this work (particularly by Gladden and Taber and also by Burtless (1995)). But the lessons learned from this work are limited by the constraints of the dataset, which not only contains very little information on the characteristics of the employers of these workers but also is too small scale to

[1] See Topel and Ward (1992)

analyze employment dynamics for different groups of low-wage workers, particularly adults. Furthermore, much of the data are from the 1980's, though low-wage labor markets have likely evolved a good deal since that time.

Other studies have focused on the role of employer characteristics or employer hiring behavior in determining which less-educated workers get hired into different kinds of jobs (e.g. Bishop, 1993; Holzer and Ihlanfeldt, 1996); and on the role of employers in the wage-determination process (Groshen, 1991; Abowd, Kramarz, and Margolis, 1999; Abowd and Kramarz, 1999; Lane, 2000). The latter, in particular, represent the latest in a long tradition of work that focuses on the "person" v. the "job", and on the extent to which there are "good" v. "bad" jobs for the same less-skilled individuals.[2] Some of these papers have used data from particular surveys of employers and/or matched data on employers and some of their employees. However the first set of studies in this body of work used fairly small samples, often limited to particular firms or sectors of the workforce; while the work on larger samples has either been cross-sectional in nature or not focused on low-wage workers per se, or both.

This paper presents evidence on low-wage workers and their jobs and earnings from an important new source of data: data from the Longitudinal Employer-Household Dynamics program (LEHD) currently being compiled at the U.S. Census Bureau. The data from this program match the universe of Unemployment Insurance wage records over the 1990's or earlier to data from the various household and economic surveys of the Census Bureau, as we describe below. The data have been transformed to allow us to analyze a wide range of issues regarding workers, their employers, and the interactions between them. Below, we use data from five states (California, Florida, Illinois, Maryland and North Carolina) over the 1990's to consider these issues.

The next section below describes the LEHD data, especially from the five states included in this analysis. Next we describe the analyses which we present on these data, followed by the results. We close with a summary and the implications of the results presented here for welfare-to-work programs and for promoting the success of low-wage workers more broadly.

[2] This tradition includes the "dual labor markets" literature of the 1970's (e.g. Doeringer and Piore, 1971) as well as the "efficiency wage" literature of the 1980's (e.g. Katz, 1986).

2 LEHD Data

In this study we take advantage of the development of a new database at the US Census Bureau that permits us to fully describe the interactions between workers and firms. This new database enables us to match workers with past and present employers, together with employer and worker characteristics.

The core of the dataset is the Unemployment Insurance (UI) wage record file. Every state in the U.S. collects quarterly records of the employment and earnings of the UI covered workforce (approximately 98% of employment in each state). These data consist of an employer identification number, and individual identification number and the earnings of that individual while employed. This permits the construction of a dataset longitudinal in both employers and employees, which have been extensively described and used elsewhere (see Burgess, Lane, and Stevens, 2000). There are several advantages over household based survey data. In particular, the earnings are quite accurately reported: there are financial penalties for misreporting. The data are relatively current, and the dataset is extremely large. Since we have almost the full universe of employers and workers, we can track movements of individuals across earnings categories and across employers with a great deal of accuracy.[3] In addition, information on industry, ownership, location, and firm size come directly from the employer, rather than self-reported by the individual. The LEHD program currently houses data from a number of states comprising 60 percent of total U.S. employment.

These data are markedly different from the household survey data that many researchers are familiar with. In particular, since the data are administrative in nature, many of the usual measures are not available. For example, earnings refer to quarterly earnings, and neither wage rates nor hours worked are typically available. In addition, UI data lack even the most basic demographic information on workers. However, the LEHD program at the US Census Bureau has worked to address these deficiencies by integrating the UI data with administrative data consisting of data on date and place of birth, gender, race and residency for almost all the workers in the data. In addition, the UI data are integrated with rich survey data such as CPS and the SIPP, providing rich survey information for a limited sample of individuals.

A major new advantage of the dataset is that LEHD staff have exploited the longitudinal and universal nature of the dataset to estimate jointly fixed

[3] The coverae in UI data is about 98 percent of total wage and salary civilian jobs. See Stevens (2002) for details about non-covered employment.

worker and firm effects, using the methodology described in detail in Abowd, Lengermann, and McKinney (2002) and in Abowd, Creecy, and Kramarz (2002). The human capital measures derived from this work can be thought of as the market value of the portable component of an individual's skill and includes some factors that are often observable, such as years of education and sex; and some factors that are typically not observable even in rich survey data, such as innate ability, "people skills," "problem solving skills," perseverance, family background, and educational quality. The firm specific component measures the wage premia associated with firm-specific factors, which may be due to a number of factors such as physical capital, organizational structure, managerial skills, rent sharing and unionization.

It is worth emphasizing just how important these new measures are. Traditional surveys of workers that measure the "kitchen sink" of demographic characteristics - such as education, occupation, age, sex, marital status and even include some firm characteristics such as firm size and industry – are typically able to explain some 30% of earnings variation. With these new measures of individual and firm-specific wage premia we are able to explain 90% of earnings variation.

In our analysis we use data for five large states, California, Florida, Illinois, Maryland and North Carolina – consisting of almost 1 billion quarterly observations, on some 58 million individuals and 3 million employers over the period 1992-99. We use a subset (summarized in Appendix Table 1) of workers aged 25-54 and with some labor force attachment in the 1993-95 period that we further describe below. This subsets the dataset to about 500 million observations on 19 million individuals and 1.2 million employers. In order to reduce computational burden, we take a 5 percent random sample of this larger dataset, which leaves us with about 1 million individuals. About 800,000 of these individuals are also observed with a labor force attachment in the 1996-98 period.

Later in the analysis, we want to compare the quarterly outcomes of those who began a new job sometime in 1995 that was different from the job held in 1994 with those who stayed on the same job. Of the 938,226 individuals in the dataset, the bulk stay with the same firm (i.e., 716,362); but 121,039 individuals change jobs over the period, and 100,825 are in neither group (i.e., they are individuals who do not show up in data in the subsequent period). To examine the outcomes of job changers and job stayers with equal precision, we choose a 50% random sample of job changers (60,520), and then randomly choose an equally number of job stayers. This gives a subset of 121,040 individuals, employed by a total of 90,857 employers, and 1,980,571 quarterly observations.

How does this sample compare with 1990 Census data? We compared the characteristics of the full sample of UI data in 1994 (with age and labor force restrictions) to the 1990 Census for all workers in our five states, with the same age restrictions. We report the results in the Appendix: briefly, UI data are very consistent with Census data. Just under half of the sample are female; about 69% White, 12% Black, and 20% "other". Just under 20% are foreign born. The industrial distribution is also very similar. 17% of employment is in manufacturing, 14% in retail trade, and about 1/3 of all workers are in the service sector. Annualized earnings are similarly consistent: average earnings in the 1990 Census were $35,393 while in UI data, they were about $35,368.

3 Description of Analysis

Our primary interest in this work is to analyze the labor market experiences of low-wage workers, particularly focusing on the way in which their interactions with employers influence the extent to which they succeed or fail in this market. Clearly, an important first step is to identify which workers can be categorized as low-wage workers. The.second step is to identify what is "success" or "failure", and the third to identify their employer and employer characteristics.

We begin by developing a definition of low-wage workers that accurately captures a group facing persistent problems of low earnings. The literature has based such definitions on household-based surveys, such as the decennial census or CPS data – often using demographic information (such as education) or low hourly wages for identifying those with earnings difficulties. Because these are cross-sectional in nature, they are unable to capture whether workers are persistently low-wage. In particular, it might capture those with *transitory* earnings difficulties (such as those returning to the labor market after a lengthy absence, or those who have been recently displaced from higher-paying jobs). Our longitudinal data can identify whether workers have persistently low earnings. However, since we only have quarterly records to measure earnings, we cannot identify those with low hourly wages as opposed to those with few hours worked per quarter. Consequently, we face a different set of identification problems, such as the risk of including those with low earnings who have chosen *voluntarily* to work few hours (such as homemakers, students or the elderly).

In order to develop a satisfactory definition, we need an analysis plan that correctly identifies workers with persistent difficulties but still allows their labor market outcomes to improve over time. We also need to avoid selecting a sample based on observed outcomes since this would seriously bias any parameters that we estimate and distort any analysis in which we engage. We therefore define workers with low earnings as *those who persistently have low earnings – here defined as $12,000 or less per year in real terms – during a 3-year base period of 1993-95.*[4] The 3-year period over which these low earnings are observed enables us to avoid those with transitory earnings problems. While the level of earnings defined here is quite arbitrary and somewhat low, we chose a level that implies poverty-level earnings, even after being supplemented by the Earned Income Tax Credit. We checked the robustness of this cutoff (and others, similar thresholds) by examining the characteristics of a sub-sample of workers whose UI earnings records were linked to the March CPS. The hourly wages, demographics and household income of this sample of workers also suggested persistent labor market problems from the more traditional, household survey based approach.[5]

To further ensure that we are targeting workers with persistent labor market difficulties not of their own choosing, we limit our sample to *prime-age* workers – i.e., those aged 25-54. In doing so, we omit age groups that are likely to contain large numbers of students or near-elderly individuals choosing to work part-time. While our sample might still include large numbers of homemakers who are working part-time, particularly while caring for children, we very often stratify our sample by gender (and/or race as well) to check whether or not our results hold for men as well as women (and for minority women as well as white women, where the latter are more likely to be more-educated women married to high earners). But, to ensure that workers have at least some consistent labor market attachment, we also limit the sample to individuals who have at least one quarter of earnings in each year of the analysis.

The second step is to characterize "success" or "failure" in this labor market. We recognize that small and/or transitory increases in earnings above this cutoff level do not necessarily imply labor market success. Thus,

[4] Nominal Earnings each year are adjusted by the Consumer Price Index for Urban Workers (CPI-U), with results presented in 1998 dollars. Since the CPI tends to overstate inflation somewhat, real earnings gains will be somewhat understated, as we note below. But comparisons across groups in tendency to escape low-earnings status or in real wage gains will not be affected by the upward bias in CPI.

[5] This earnings cutoff generated a sample of workers among whom the vast majority had no college education, most household incomes were under $20,000, and wages averaged about $8 per hour. Details are available from authors.

we also define two intermediate categories of earnings: those with *partial low-earnings*, who might have earned above \$12,000 per year in one or more of the years in the base period, but never earned above \$15,000; or those with *partial non-low earnings*, who might have earned above \$15,000 but did not do so consistently. Those with consistent *non-low earnings* are thus those who earn above \$15,000 each year in the base period.

Having defined this sample and base period, we then analyze earnings outcomes during a *subsequent* period, and especially look for evidence that the earnings difficulties observed in the base period have eased somewhat. We do so in two ways: first, we analyze a subsequent 3-year period (i.e., 1996-98), and measure the extent to which workers with low earnings in the base period have either *partially or completely escaped* this status. We define "partial escapes" as those in which the individual had partially low or partially non-low earnings in the later period – i.e., earnings at least sometimes above \$12,000 but not consistently above \$15,000 per year. In contrast, "complete escapes" from low earnings status involves those who consistently earn above \$15,000 per year in the later period.

A second way in which we analyze the subsequent labor market success of those with persistently low earnings in the base period is to compare earnings on jobs held during or after 1996 with those on jobs held before that time. Of course, the primary job held in 1996 may be the same one held earlier or a different one; consequently, we now define "job-changers" as those who began a new job sometime in 1996 that was different from that held in 1995, while "job-stayers" are those whose jobs were the same in both years.

The designation of low-earning status based on the 1993-95 period remains the same as before –i.e., we still stratify the sample into those with persistently low earnings in this period v. those whose earnings are higher; but we now measure labor market outcomes by earnings on first job held during the subsequent period (from 1996 quarter 1 to 1999 quarter 4) v. the last one held in the base period (from 1992 quarter 1 to 1995 quarter 4), where these two might be the same or different jobs.[6] This analysis thus enables us to consider jobs of potentially shorter duration than in the earlier analysis, and to measure earnings levels and changes continuously rather than discretely (which enables us to avoid the problem of arbitrary categories mentioned above). The analysis now also focuses directly on the

[6] A sample of jobs that either begin or end within a certain period constitutes a random sample of jobs that do not suffer from the overrepresentation of longer-duration jobs in a sample taken at any point in time. Limiting those samples to those with low earnings during the base period has implications that we discuss below.

earnings of the primary job, rather than the total earnings of a 3-year period in which one or more jobs might have been held.

We thus address the third definitional issue posed by the use of this new dataset – that of defining their employer. Since workers might well have had more than one job in either or both of these 3-year periods, we focus on their *primary* employer during each period – i.e., the one with whom they had the highest earnings per quarter in the most quarters during each period. Much of the analysis will then focus on those who had the same primary employer in both periods (i..e., "job-stayers") as opposed to those whose primary employer had changed (i.e., "job-changers"). A similar analysis of industry changers and stayers will be included as well.

Having set up our definitions, we now proceed with a three-part analysis. First, we describe the demographic characteristics of workers in the different earnings categories during the 3-year base period of 1993-95 as well as the characteristics of the firms for which they work. Second, we analyze worker transitions into higher earnings categories between the 1993-95 and 1996-98 periods, particularly focusing on how these transitions are related to both worker and firm characteristics. Third, we compare the wage levels and changes for jobs held in1995 and thereafter with the wage levels and change for jobs held in 1994 or earlier, for two groups of workers: those that are low earners during the 3-year base period and those that are not.

4 Empirical Results

4.1 Workers and Jobs in the Base Period, 1993-95

We begin with an analysis of workers during the base period of 1993-95, during which workers are categorized as low earners or non-low earners (or some intermediate categories). We consider their own demographic characteristics, as well as those of their primary employers, during this time period as well.

Table 1 presents the distribution of workers in our sample of prime-age workers in five states across four earnings categories: The four earnings categories are:

1. Low - i.e., earnings of $12,000 or less in each of the 3 years;

2. Partially Low – i.e., with earnings above $12,000 in at least one year but never above $15,000;

Table 1: Distribution of workers across earnings categories in 1993-95

	Low earnings*	Partially low earnings*	Partially non-low earnings*	Non-low earnings*	All
All	12.22	5.81	20.54	61.44	100.00
Female	16.03	7.44	21.41	55.12	100.00
Male	8.78	4.34	19.75	67.13	100.00
Older**	10.81	5.20	17.48	66.51	100.00
Younger**	14.50	6.80	25.49	53.21	100.00

* A worker is defined as having "low earnings" if real (deflated by CPI-U) annual earnings from all employers are below $12,000 (in 1998 U.S. dollars) in all three years. A worker is defined as having "partially low earnings" if total annual earnings are below $15,000 in all three years. A worker is defined as having "partially non-low earnings" if total annual earnings are above $15,000 in at least one but not all three years. A worker is defined as having "non-low earnings" if total annual earnings are above $15,000 in all three years. Only workers who reports earnings in at least one quarter in each of the three years and who are between 25 and 54 years old in 1994 are included in the sample.

** The "Older" category includes workers who are between 35 and 54 in 1994 and the "Younger" category includes workers who are between 25 and 34 years old.

3. Partially Non-Low – i.e., earnings above $15,000 at least once but not in all three years; and

4. Non-Low – i.e., earnings above $15,000 in all years.

The distribution is presented for all workers, and separately by gender and by age group (where "older" and "younger" workers are defined as those aged 35-54 and 25-34 respectively).

The results indicate that roughly 12 percent of prime-age workers during this time period consistently had very low earnings in the labor market. Another 6 percent or so have partially low earnings and 21 percent have partially non low-earnings. Thus, nearly 40 percent of the total sample exhibits annual earnings below $15,000 for at least one of the three years.[7]

[7] The fraction of workers with persistently low earnings is somewhat sensitive to how we limit the sample in terms of job attachment. Where we condition on at least two quarters of work each year instead of one, we find significantly smaller percentages of low earners. However, the qualitative results discussed below, in terms of the correlates of low earnings and escapes from low-earnings status, are very robust to these sample changes.

Table 2: Distribution of workers across earnings categories in 1993-95: by race/gender or place of birth

	Low earnings	Partially low earnings	Partially non-low earnings	Non-low earnings	All
All	12.22	5.81	20.54	61.44	100.00
White Female	14.58	6.61	20.91	57.90	100.00
White Male	6.39	3.06	17.80	72.76	100.00
Black Female	19.00	9.01	22.28	49.72	100.00
Black Male	17.14	7.10	24.01	51.74	100.00
Other Female	19.16	9.34	22.60	48.90	100.00
Other Male	12.24	7.07	23.86	56.84	100.00
Foreign Born	14.19	8.06	23.26	54.49	100.00
US Born	11.78	5.32	19.94	62.96	100.00

As expected, females are much more likely to have consistently low earnings than men (16 percent v. 8 percent respectively), as are younger workers relative to older ones (15 percent v. 11 percent). Still, the fractions of prime-age men and older workers with persistent low earnings are striking here, and implies that our results are not driven completely by women who are working part-time in order to raise small children.

How do these distributions vary by race as well as gender, and by location of birthplace (US v. foreign)? Table 2 presents additional distributions broken down by these demographic characteristics. Race groups are whites, blacks and "others," with the latter representing both Hispanics and Asians. The results show, again as expected, that blacks and other non-white minorities are much likely than whites to suffer from persistently low earnings, as are foreign-born workers relative to those who are US-born. Within each racial group, women are more likely than men to be low earners, though the gap in incidence of low earnings between black women and black men is small.

Indeed, black men are more likely to suffer from persistently low earnings than are white women. It is likely that the latter group contains the largest fraction of individuals working part-time because of responsibilities in the home. The relatively weak earnings of black men may well represent their weak attachments to the labor market, which continued to deteriorate in the decade of the 1990's while those of black women grew stronger (Holzer and Offner, 2002). In contrast to blacks, the tendency of "other" men to have low earnings is significantly lower than that of "other" women, likely indicating a stronger attachment to the labor market for the men of these groups relative to black men. Finally, while white men had the lowest incidence of consistently low earnings (6 percent), even for them the rates are not trivially low.

In what sectors of the economy are these workers with low-earnings most likely to be found? Table 3 presents data on the distribution of low-earnings workers across 2-digit nonagricultural industries, based on their primary employers during the period 1993-95.[8] In the first column, we present the actual distribution across industries – i.e., the percentages of all low-earners found in each industry, ranked in descending order from highest to lowest among the 20 industries listed. In the second column, we present the percent of workers within each industry who are low-earners (rather than the distribution of low earners between industries). The two methods needn't generate identical rankings of workers across industries, since large industries without high concentrations of low-earners can still account for significant fractions of all such low earners in the labor market. Thus, the second category is a more accurate reflection of industries with low average wages (or at least large concentrations of low-wage workers), while the first reflects both relative wages and sizes of the industries themselves.

The results of Table 3 show that "eating and drinking places" account for the largest percentage of all low earners of any 2-digit industry (about 15 percent) and have the highest concentration of low earners within the industry (over 40 percent). More generally, we find that low earners are concentrated in a fairly small number of industries. In fact, three industries - eating and drinking, business services, and educational services - account for over a third of low earners, while seven industries account for over half. Though business services are not generally low-wage industries, they include "temp" agencies, which account for the bulk of low earners within the industry.[9] Education and health services are also not particularly low-wage industries, though they account for large fractions of low earners by virtue of their size and tendency to have particular occupations with large numbers

[8] It is worth pointing out that a relatively large fraction of workers with low earnings are concentrated in agricultural industries. However, Agricultural workers are omitted becuase of their inconsistent coverage by the UI system across states. Mining is also omitted as a category because of its very small size, especially for low earners.

[9] Other more-detailed industries within business services include, but are not limited to, advertising; consumer credit reporting agencies; services to dwellings and other buildings; and computer programming and data processing. The percentage of low earners in the business services accounted for by temp agencies in the base period is 52%. In much of the analysis that follows, we focus on those working specifically for temp agencies within this category.

Table 3: Distribution of low earners across industries

Major Group (2-digit SIC)	Percentage of low earners in each industry	Percentage of workers in each industry who are low earners
58 Eating and drinking places	14.62	40.69
73 Business services	11.46	22.43
82 Educational services	9.28	14.73
80 Health services	5.83	7.65
83 Social services	3.60	23.81
54 Food stores	3.56	17.57
59 Miscellaneous retail	3.53	20.86
53 General merchandise stores	3.43	22.71
17 Special trade contractors	3.08	11.07
70 Hotels, etc.	2.94	24.76
72 Personal services	2.39	30.71
79 Amusement and recreational services	2.36	22.45
23 Apparel and other textile products	2.34	30.31
51 Wholesale trade—non-durable goods	2.00	7.76
50 Wholesale trade–durable goods	1.65	4.30
55 Automotive dealers and gas stations	1.62	10.19
65 Real estate	1.59	13.14
20 Food and kindred products	1.56	12.27
87 Engineering and management services	1.51	5.69
56 Apparel and accessory stores	1.28	21.32
All other industries	20.37	5.97

Industry reflects the industry of the primary employer in the three-year period, where the primary employer is defined as the employer with which the worker has the highest earnings in the largest number of quarters in the three-year period.

of low-wage workers.[10]

In contrast, a number of other industries – such as hotels and other lodging places, personal services, amusement services, and general merchandise stores – have large concentrations of low-earners within the industry but do not account for large fractions of low earners overall, apparently due to their relatively small sizes. Almost all industries with high concentrations of low earners are in the retail trade and service sectors, although there are a few important exceptions. In particular, apparel and textile products manufacturing has over 30% of its workers having consistently low earnings. Real estate is another field with a major concentration of low earners (13%), though this may also reflect a high degree of part-time work.

What are some other characteristics of firms that have large numbers of low earners? In Table 4 we consider the distributions of workers in each of our four earnings categories across categories of firms based on size, employment growth or decline (the "job flow" rate), a measure of turnover (the "churning rate"), and firm wage premia.

What are the reasons for including these measures of firm characteristics? Firm size is known to have a strong effect on average wages, even controlling for observable characteristics of workers (Brown, Hamilton, and Medoff, 1990).[11] Anecdotal evidence, as well as some empirical evidence (Theeuwes, Lane, and Stevens, 2000) suggests that firm expansion and contraction are likely to affect worker outcomes. We therefore examine the effects of the "job flow rate", measured as the change in employment between the beginning and end of a period divided by the average size of the firm over that period.[12] We also use firm turnover as an observable firm characteristic likely to affect worker outcomes (Lane, 2000; Lane and Stevens, 2001). Here we use a measure of turnover net of that required for the firm to achieve a different employment level: "churning". This is defined as the difference between the sum of accessions and separations, on the one hand, and the absolute value of job flows, on the other, all divided by the average size of the firm.[13] The fact that job turnover is negatively correlated with wages is

[10] Low-wage jobs in health care include nurses' aides, home health aides, and orderlies. In education these jobs include janitors, cooks, and part-time bus drivers.

[11] Our measure is one of firm size, not establishment size. However, single establishment firms employ 70% of all individuals.

[12] For instance, if employment in a firm increases from 50 to 150, the job flow rate is 1 =(150-50)/0.5*(150+50) or 100 percent. Values, thus, represent percentage change in employment relative to average size over the period. This variable is bounded between –2 and 2, where the endpoints correspond to firm exit and firm entry respectively.

[13] This is a measure of worker turnover in excess of what is needed to accommodate the net employment change. For instance, using the same example as before, if the firm

well-established in the literature on labor markets, though its direct causal effect is somewhat less clear.[14] Finally, following the work of Kremer (1993) and Kremer and Maskin (1996) which suggests a theoretical basis for the sorting of high workers to high wage firms and the work of Abowd, Kramarz, and Margolis (1999) and Abowd, Finer, and Kramarz (1999) which present empirical evidence in support of this, we examine the effect of the firm wage premium - a fixed firm effect which captures the amount each firm pays its worker above or below their market wage.[15]

The results of Table 4 clearly show that low earners are more heavily concentrated in small establishments than in larger ones, which is consistent with the earlier literature. Likewise, low earners are much more heavily concentrated in high-turnover establishments than in low-turnover ones. However, the relationship between net job flows and earnings is somewhat less clear. Low earners are relatively concentrated both among firms entering and exiting the market. They are also somewhat more concentrated among firms with significant positive or negative net employment growth (relative to those with modest amounts of either in the -.1 to .1 range).

The strongest relationship of all exists between the incidence of low earners and firm wage premia. For instance, about 70% of non-low earners work for firms whose wage premia are positive (a zero premium reflects the average employment-weighted firm). But among those who are consistently low earners, only about 16% work for firms with positive premia, while 24% of partially low earners do so. The preliminary evidence thus suggests that the *low earnings of workers are a result of two related factors: their own low level of skills and the disproportionately low wages paid by the firms for which they work.* Given this, plus the fact that these premia are highly correlated with industry and also with turnover and other firm characteristics (Krueger and Summers, 1987; Holzer, Lane, and Vilhuber, 2002), this

increases employment from 50 to 150 through 120 accessions and 20 separations, then the worker churning rate is 0.4 = [120+20-abs(150-50)]/0.5*(150+50) or 40 percent. Values, thus, represent worker churning relative to average size over the period. This variable takes on only positive values and does not have an upper bound.

[14] See Holzer and Lalonde (2000). Job turnover is clearly endogenous with respect to low wages across individuals, and may contribute to these low wages by reducing job tenure. However, firm-level turnover is likely more exogenous with respect to the earnings of individual low earners in those firms.

[15] The firm wage premium is derived from a regression of log earnings on a full panel of individuals matched to firms, in equations that control for person fixed effects, experience interacted with gender and a full set of time dummies. The firm wage premia is the coefficient on the firm dummy variable in each case. See Abowd, Creecy, and Kramarz (2002) for a fuller description.

Table 4: Distribution of workers across firm characteristics

Limits of each category	Low earnings	Partially low earnings	Partially non-low earnings	Non-low earnings
		Firm size*		
(0,20]	26.12	22.40	21.15	13.27
(20,50]	11.34	11.68	11.56	8.97
(50-100]	8.65	9.84	9.59	8.12
(100,500]	18.67	21.63	21.92	20.82
(500,∞)	35.21	34.46	35.77	48.81
		Job flow rate*		
Firm exit	2.60	2.41	2.62	1.77
(-2, -1]	1.84	1.47	1.91	1.18
(-1,-0.5]	2.83	2.33	2.41	1.37
(-0.5,-0.1]	13.87	13.52	13.96	12.93
(-0.1,0.1)	48.64	50.54	48.34	60.22
[0.1,0.5)	21.86	22.06	22.44	17.96
[0.5,1)	3.70	3.14	3.59	1.77
[1,2)	1.86	1.74	1.82	0.86
Firm entry	2.80	2.79	2.90	1.93
		Worker churning rate*		
[0,0.1)	4.07	6.32	13.18	30.50
[0.1,0.2)	13.99	17.59	23.22	31.25
[0.2,0.5)	32.66	39.11	35.66	26.68
[0.5,1)	27.38	24.15	17.79	8.28
[1,2)	14.36	9.40	7.43	2.62
[2, ∞)	7.53	3.42	2.71	0.68
		Firm wage premium*		
(-∞,-0.15)	66.96	50.13	28.15	15.41
[-0.15,0)	16.82	23.96	19.60	14.85
[0,0.15)	9.61	16.63	22.44	22.04
[0.15, ∞)	6.60	9.28	29.81	47.69

* Defined in text.

will be the single characteristic of firms that we will focus on most closely (though not exclusively) in our regression analysis below.

Overall, we see that persistently low earnings plague a fairly large percentage of prime-age adults in the U.S. workforce, and that their earnings difficulties are associated not only with personal characteristics but also with those of the firms and industries in which they work.

4.2 Transitions Over Time Across Earnings Categories

Until now, we have used data in our 3-year baseline period of 1993-95 to document the persistence of low earnings for certain workers and the association between low earnings and various worker and firm characteristics. We now turn to an analysis of which low earners subsequently succeed in the labor market, and the role played by firms and industries in their success. This analysis is based on the subsequent 3-year period, 1996-98, and on the transitions made by workers across earnings categories between those two periods. The role of the primary employer, and especially of changes in that employer across the two periods, will be highlighted.

We begin in Table 5 with the "transition matrix" for our four earnings categories across these two periods. The matrix tells us, conditional on which category a worker was in during the earlier period, what the probability is that they will be in each of the four categories during the subsequent period. The probabilities thus sum to one (horizontally) for each category in the 1993-95 period. Table 5 presents the entire matrix for all workers in the sample, while Table 6 presents the transition rates only for those who were initially low earners by various demographic breakdowns.

The results of Table 5 indicate that *almost half of those prime-age workers with very low earnings in the 1993-95 period make a transition into one of the other earnings categories in the latter period - though most are into intermediate earnings categories.* More specifically, over 40% of those having earnings persistently under $12,000 in the early period end up with earnings sometimes over that amount, and more than half of those occasionally earn more than $15,000.[16] But only 6% of the initial low earners consistently

[16] It is, of course, possible that very small amounts of wage growth pushed many individuals from just under the cutoff for partially low earnings to just above it. However, very few individuals in the low-earnings category were close to the margin of that category (e.g., in the $11-12,000 range) in all years during the base period. Furthermore, the use of the CPI to deflate earnings over time tends to understate real wage growth and therefore generates a downward bias in the percentage of workers who escape the low-earnings category.

Table 5: Transition matrix: distribution of workers across earnings categories in 1996-98 by earnings category in 1993-95

1996-98 / 1993-95	Low earnings	Partially low earnings	Partially non-low earnings	Non-low earnings	All
			All		
Low	53.03	16.63	24.10	6.24	100.00
Partially low	16.68	25.58	39.65	18.10	100.00
Partially non-low	6.70	6.04	31.74	55.53	100.00
Non-low	0.50	0.51	9.36	89.63	100.00
All	7.40	4.36	16.44	71.80	100.00
			Female		
Low	55.93	17.54	21.44	5.10	100.00
Partially low	17.04	28.01	38.10	16.85	100.00
Partially non-low	7.46	6.96	31.92	53.66	100.00
Non-low	0.67	0.67	11.15	87.51	100.00
All	10.28	6.01	18.43	65.28	100.00
			Male		
Low	47.57	14.90	29.15	8.39	100.00
Partially low	16.06	21.43	42.28	20.22	100.00
Partially non-low	5.91	5.09	31.55	57.45	100.00
Non-low	0.37	0.39	8.02	91.22	100.00
All	4.81	2.87	14.65	77.67	100.00
			Young		
Low	45.78	16.40	29.59	8.24	100.00
Partially low	16.20	19.09	43.69	21.01	100.00
Partially non-low	6.22	5.13	31.69	56.97	100.00
Non-low	0.63	0.70	12.09	86.57	100.00
All	8.49	4.95	21.34	65.22	100.00
			Old		
Low	56.43	16.73	21.54	5.30	100.00
Partially low	16.90	28.63	37.74	16.73	100.00
Partially non-low	6.95	6.52	31.76	54.76	100.00
Non-low	0.46	0.46	8.64	90.44	100.00
All	7.03	4.16	14.81	74.00	100.00

Table 6: Transition matrix: distribution of workers across earnings categories in 1996-98 by gender/race: for those with low earnings in 1993-95

	Low earnings	Partially low earnings	Partially non-low earnings	Non-low earnings	All
White Female	56.40	16.47	21.61	5.52	100.00
White Male	46.85	13.06	29.85	10.24	100.00
Black Female	55.88	18.43	21.46	4.23	100.00
Black Male	53.96	15.38	25.50	5.15	100.00
Other Female	54.63	19.90	20.92	4.55	100.00
Other Male	44.22	17.53	30.58	7.67	100.00

make over \$15,000. The extent to which such progress reflected unique characteristics of the late 1990's – such as tight labor markets, welfare-to-work policies, expanded supports for the working poor that might have induced more work effort, etc. – is not indicated here.[17]

Table 6 indicates that significant transitions out of persistent low earnings were achieved by all demographic subgroups in that population, but at somewhat different rates. For instance, *white males appear to have the highest rates of transition out of low earnings, while blacks - and especially black males – have the lowest rates.* Understanding why the success rates of some who are persistently poor end up being better than others, and especially the role played by differential access to firms and jobs that offer better opportunities, is thus a primary goal for this work.

In Table 7 we analyze the relationship between successful transitions out of persistent low earnings and the tendency to change jobs or industries. Among those with persistent low earnings in 1993-95, we identify three groups in the 1996-98 period:

1. Those whose earnings remain persistently low;

2. Those who "partially escape" low earnings, by earnings above \$12,000 or occasionally above \$15,000 (i.e., those who become have "partially low" or "partially non-low" earnings in this period); and

3. Those who "completely escape" and now consistently earn above \$15,000 per year.

[17] For an excellent set of papers on how the tight labor market and high productivity growth of the late 1990's affected workers see the volume edited by Krueger and Solow (2002). For a review of how these forces, along with welfare reform and the expansions of the Earned Income Tax Credit affected poor single females see **?**.

Table 7: Earnings transition tates by job/industry change: for those with low earnings in base period

	Still low earnings	Partial escapers	Complete escapers	Still low earnings	Partial escapers	Complete escapers
	Changed jobs			Did not change jobs		
All	46.19	45.58	8.23	62.86	33.77	3.37
White Female	48.23	43.90	7.86	60.24	36.96	2.80
White Male	38.88	48.46	12.66	61.13	34.88	3.99
Black Female	53.80	41.28	4.92	63.53	34.40	2.07
Black Male	51.76	42.73	5.51	54.69	41.16	4.15
Other Female	46.57	46.63	6.80	65.11	31.87	3.02
Other Male	38.56	51.86	9.58	61.72	32.56	5.72
	Changed industries			Did not change industries		
All	43.66	47.36	8.98	57.56	37.53	4.91
White Female	45.36	46.15	8.49	57.11	39.32	3.57
White Male	36.62	50.06	13.32	57.69	37.35	4.96
Black Female	53.48	40.99	5.53	58.55	38.08	3.37
Black Male	49.81	44.82	5.37	49.15	44.87	5.98
Other Female	44.38	47.97	7.64	60.43	35.13	4.43
Other Male	35.88	53.58	10.53	53.80	38.05	8.15
	For those initially employed in temp agencies:					
	Changed jobs			Did not change jobs		
All	48.88	42.76	8.36	70.54	28.01	1.45
White Female	44.67	44.96	10.37	63.46	36.54	0.00
White Male	45.78	44.22	10.00	86.36	13.64	0.00
Black Female	50.76	42.61	6.63	66.07	30.36	3.57
Black Male	58.54	35.71	5.75	62.50	33.93	3.57
Other Female	44.44	46.78	8.77	59.63	38.53	1.83
Other Male	47.12	44.47	8.41	75.76	23.23	1.01

A worker is in the "Still low earnings" category if earnings are low, as previously defined, also in 1996-98. A worker is in the "Partial escapers category" if earnings are partially low or partially non-low in 1996-98. A worker is in the "Complete escapers" category if earnings are non-low in 1996-98. If the worker has different dominant employers in 1996-98 and in 1993-95, then the worker has changed jobs. Consequently, if the 1-digit industries of the dominant employers are not the same in the two periods, then the worker has also changed industries.

We also identify a variety of other groups, based on the relationship between their primary jobs in the two periods: those who changed jobs across across the two periods v. those that did not; those who changed industries (as well as jobs) across the two periods v. those that did not; and those who initially were working with a temp agency and changed jobs v. non-changers in temp agencies. The latter begins our attempt to highlight the role of temp agencies in the low-wage labor market, and especially whether or not these agencies play some role in providing greater upward mobility to low earners than they otherwise would have on their own.[18]

In Table 7, we present the probabilities of staying in low earnings, v. partially or completely escaping into higher earnings, conditional on whether or not they changed jobs, changed industries, or changed jobs through a temp agency. The sample is limited to those with persistently low earnings in the 1993-95 period. In Table 8, we present the opposite conditional probabilities – i.e., the probabilities that individuals changed jobs, changed industries, or changed jobs through a temp agency, conditional on whether or not they have partially or fully escaped low earnings. Both sets of conditional probabilities are needed to highlight the role of changing jobs/industries and the role of temp agencies in improving success rates of persistent low earners. All results are presented for the entire sample of low earners and also by separate race/gender groups.

The results of Table 7 indicate that:

- Those who change jobs and especially industries have higher rates of transition out of low earnings that those who stay in the same jobs or industries;

- Those who change jobs through temp agencies also have higher rates of transition out, especially relative to non-job-changers in temp agencies (though the success rates of job-changers here seem comparable to those changing jobs/industries more generally);

Thus, the percentage of initially low earners who completely escape this status is 8% among changers and only about 3% among the non-changers. For white males, success rates among job/industry changers are 13% and

[18] See Autor and Houseman (2002) andLane, Mikelson, Sharkey, and Wissoker (2001) for reviews of evidence and general discussion of these questions. While it is clearly that workers in temp agencies earn relatively lower wages and benefits than comparable workers, there have been continuing questions about whether or not the future earnings of temp workers are improved by the quality of job placements and any additional work experience generated for them by the temp agencies.

Table 8: Job/industry changes by transition from low earnings in base period

	Still low earnings	Partially escapers	Complete escapers
Percent of transitions that involve job change			
All	51.33	65.95	77.80
White Female	44.15	59.51	73.51
White Male	54.05	73.53	80.52
Black Female	65.17	70.06	78.66
Black Male	73.37	79.94	81.82
Other Female	44.74	59.95	78.41
Other Male	56.61	69.99	81.04
Percent of transitions that involve industry change			
All	25.28	36.47	45.48
White Female	20.52	31.53	40.07
White Male	29.64	45.35	50.86
Black Female	30.47	33.23	42.43
Black Male	41.44	50.52	47.66
Other Female	21.29	31.40	45.64
Other Male	28.20	39.47	49.82
Percent of transitions that involve job change; temp work in base period			
All	82.59	91.27	97.53
White Female	82.67	88.14	97.30
White Male	79.62	92.48	98.46
Black Female	89.04	92.21	100.00
Black Male	79.87	93.88	100.00
Other Female	80.42	90.40	93.75
Other Male	85.89	91.36	95.00

roughly 4% among the non-changers. In contrast, the rates of complete escape for black males with persistently low earnings in the initial period are generally 6% among changers and 4% among non-changers. Interestingly, white males do no better than black males in escaping low-earning status among those who stay in their former jobs or even their former industries; it is their greater success than others when changing jobs that generates their higher rate of escape from low earnings overall.

The conditional probabilities in Table 8 shed further light on this issue. Overall:

- *Over three-fourths of those who completely escape low earnings did so through a job change*, and nearly two-thirds of those who partially escape did so, while just over half of those who remained very low earners changed jobs;
- *Nearly half of the complete escapers, and over a third of the partial escapers*, changed industry (as well as job), while just a quarter of those who remained low earners changed industry.
- The vast majority of workers in temp agencies ultimately changed jobs, and job change rates were virtually universal among those successfully escaping low earnings.

The data thus indicate that *changing jobs and especially changing industries are important components of achieving success in the low-wage labor market*. But a few important caveats are also in order. For one thing, many job changes and even industry changes do not result in successful escapes for low earners; thus changing jobs is no guarantee of success. Also, a significant fraction (i.e., one-fourth to one-third) of those who do escape do so on the jobs that they initially had. Thus, both avenues to success among low earners need to be explored in greater detail.

In Table 9 we present the distribution of initially low-earning across industries in the later (1996-98) period. We present separate distributions for job-stayers, job-changers, and job changers through temp agencies, subdivided in each case by whether or not they escaped their low earnings (partially or completely). Thus, we present nine distributions across all nonagricultural (and nonmining) 1-digit industries, as well as selected 2-digit industries. To interpret the results, it is important to compare the concentrations in specific industries across the nine groups, to see where successful or unsuccessful job-stayers or job-changers are most likely to be found.

Table 9: Distribution across major SIC dvisions and selected major group industries in 1996-98 by transitiona and job mobility: for those with low earnings in base period

	Job stayers			Job changers			Job changers thru temp agencies		
	Still poor	Partial escape	escape	Still poor	Partial escape	escape	Still poor	Partial escape	escape
Construction	3.00	4.39	7.98	3.81	6.39	7.37	3.81	6.22	5.43
Manufacturing	8.28	10.58	9.12	8.27	13.67	15.46	10.32	20.26	25.36
-Food etc	2.81	1.77	0.83	1.20	1.25	1.07	1.05	2.03	2.90
-Apparel	2.29	2.09	0.41	2.48	1.71	0.51	1.91	1.38	0.36
-Printing & publishing	0.72	0.94	1.35	0.64	1.15	1.58	0.66	1.45	2.54
-Electrical equip.	0.27	0.78	0.62	0.46	1.40	2.11	0.85	2.68	1.81
-Other Mfg industries	2.18	4.99	5.91	3.49	8.16	10.20	5.85	12.74	17.75
TCU	2.22	3.15	4.66	2.92	4.74	5.50	2.37	5.35	6.52
-Local passenger transit	0.57	0.77	0.73	0.72	0.79	0.59	0.33	0.58	0.00
-Motor freight transp.	0.68	0.74	1.14	1.00	1.52	1.81	0.86	2.39	2.90
-Transportation by air	0.32	0.83	1.14	0.45	0.71	0.62	0.72	0.51	0.36
-Transportation services	0.31	0.37	0.52	0.30	0.51	0.59	0.20	0.51	0.72
-Other TCU	0.35	0.45	1.14	0.45	1.21	1.87	0.26	1.37	2.54
Wholesale	2.76	3.71	5.28	3.27	5.54	6.90	3.35	7.74	7.61
Retail	27.23	26.17	15.23	31.05	22.20	11.50	18.73	13.46	5.80
-Merchandise stores	2.62	2.98	1.86	3.17	3.06	1.46	1.84	1.38	0.73
-Food stores	3.46	4.53	2.49	3.73	2.81	1.22	2.04	1.67	0.00
-Eating & drinking	13.90	11.76	5.08	16.71	8.61	3.09	10.91	4.92	2.18
-Misc. retail	3.81	3.32	2.07	3.15	2.60	1.63	1.71	1.88	0.73
-Other	3.44	3.59	3.73	4.29	5.12	4.10	2.23	3.62	2.18
FIRE	2.82	3.19	4.56	2.59	4.97	7.10	1.45	4.99	7.61
Services	51.58	47.51	49.84	47.07	40.81	43.16	59.26	40.30	38.41
-Hotels etc.	2.40	2.31	2.38	3.45	2.42	1.48	1.71	1.08	0.36
-Personal services	3.01	2.16	1.66	2.41	1.51	0.83	1.32	0.65	0.36
-Business services	4.91	4.84	5.18	17.02	10.77	9.66	44.74	21.13	17.76
-Health services	5.28	7.34	7.36	5.81	9.03	10.46	2.89	6.29	6.52
-Educational services	20.02	18.78	21.03	6.02	5.02	7.76	1.71	2.60	3.26
-Social services	4.48	4.30	3.01	3.61	3.80	2.50	2.36	2.53	1.45
-Other Services	11.49	7.79	9.22	8.76	8.26	10.46	4.53	6.00	8.70
Public Administration	2.12	1.30	3.32	1.01	1.68	3.00	0.72	1.66	3.26
All	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

A number of findings emerge from this table.

- *Among both job stayers and changers, those who are initially low earners subsequently do quite well in the "traditional" industries such as construction, manufacturing, transportation/communications/utilities (TCU) and wholesale trade.* These are, of course, relatively high-wage industries, even after controlling for the personal characteristics of employees there (Krueger and Summers, 1987). Thus, initially low earners who stayed in their jobs and escaped low earnings are much more heavily concentrated in these sectors than in retail trade or the services; while those who changed jobs and escaped low earnings are more heavily concentrated in these sectors than the others as well.

- *Temp agencies seem to place a relatively large number of the initially poor in these industries, particularly manufacturing, and enjoy high success rates when they do.* The concentrations of initially low earners in manufacturing are substantially higher among job changers through temp agencies than among job changers and stayers more broadly; and they are more than twice as likely to be concentrated there among those who escaped low earnings (either partially or completely) than among those who stayed. To a lesser extent, the same story can be found in TCU, wholesale trade, and the financial services (FIRE).

- *Within manufacturing or the services, some sectors are clearly better than others from the vantage-point of initially low earners.* For instance, those who successfully escape low earnings are somewhat more concentrated in *health services* (and, to a lesser extent, *educational services*) than are those still poor: these are fairly good sectors for job stayers and also for job changers to enter. In contrast, those who are still low earners are more heavily concentrated in *apparel and other textile* industries than in any other manufacturing industry, regardless of whether they stayed on their jobs or changed them. The unsuccessful are relatively more concentrated in eating and drinking places than any other 2-digit industry, while those newly moving into the business services sector are heavily concentrated among those still earning little as well. Thus, temp agencies may serve as a successful launching pad to other industries, even though it does not confer immediate success on those entering it.

In Table 10 and Table 11, we continue to analyze the distributions of initially low earners who either subsequently succeeded or did not succeed

Table 10: Distribution across major SIC dvisions by race/gender and earnings transitions in 1996-98: for those with low earnings in base period

	Constr.	Manuf.	TCU	Wholes	Retail	FIRE	Services	Public
Still low earnings								
White Female	1.60	4.56	1.99	2.65	32.77	3.21	51.43	1.79
White Male	8.79	5.73	4.19	3.42	27.25	3.03	44.91	2.69
Black Female	0.75	6.43	2.21	1.44	23.98	1.81	61.89	1.49
Black Male	9.03	7.31	5.10	3.05	23.88	2.17	48.32	1.14
Other Female	1.02	19.60	1.53	4.23	24.63	2.27	46.09	0.63
Other Male	6.13	15.00	2.90	4.15	33.13	1.95	36.26	0.48
Partial escapers								
White Female	2.33	7.32	3.08	3.75	26.65	5.65	49.53	1.70
White Male	14.07	10.21	6.54	6.06	23.75	3.26	34.08	2.03
Black Female	0.68	10.71	4.09	2.66	17.87	4.95	56.86	2.18
Black Male	9.44	14.57	7.21	5.95	19.22	3.24	38.82	1.55
Other Female	1.53	22.23	2.49	5.88	21.46	3.58	42.04	0.79
Other Male	10.98	21.50	4.57	7.01	23.66	3.05	28.49	0.75
Complete escapers								
White Female	3.29	10.01	3.04	4.07	11.69	8.27	56.33	3.29
White Male	13.59	14.68	6.34	7.92	13.43	4.92	35.95	3.17
Black Female	1.61	12.86	4.18	2.25	9.00	9.65	54.34	6.11
Black Male	7.28	13.79	11.11	8.05	11.11	5.36	39.85	3.45
Other Female	2.65	14.57	5.74	8.17	13.69	8.61	44.59	1.99
Other Male	13.46	24.24	7.00	10.77	13.11	2.33	27.83	1.26

in the labor market across industries in the later (1996-98) period. Now we do so separately for race/gender groups. Thus, Table 10 presents these distributions across 1-digit industries, while Table 11 does so for selected 2-digit industries.

The results of Table 10 indicate:

- *Males within each racial group are more likely than females to be found in the "traditional industries, especially among those escaping low earnings status.* The opposite is true for females in FIRE and the services. In fact, the latter two services account for about 50-60% of those escaping low earnings among women but 30-40% among men.

- *While the broad patterns of escape are similar across racial groups, some interesting differences emerge as well.* For instance, white males and other males (especially Hispanics) are more likely than other groups to escape low earnings through construction; other males are relatively most likely to escape through manufacturing; while TCU seems to work relatively well for black males. In contrast, black females escaping low earnings are relatively concentrated in the FIRE sector, while white and black females both do relatively well in the services also. In contrast, other females escaping low earnings are more likely found in manufacturing and even retail trade than white or black females.

These differences across race and gender lines can be explored in greater detail in Table 11, which presents similar data for selected 2-digit industries - but only for those who escaped (partially or completely) their initial low earnings status.[19] Here we get a somewhat clearer picture of the jobs and sectors through which different groups escape low earnings. For instance, the success of black men in the TCU sector can be seen in local passenger transit and motor freight transportation – i.e., *bus and truck driving* – as well as air transport (where they are presumably likely to be baggage handlers or in maintenance). White females in retail trade have somewhat higher success rates than other groups in general merchandise and food stores (i.e., *department stores and supermarkets*), while other males escape more frequently (though mostly partially) through the low-wage restaurant sector, perhaps by working long hours. In the services, white females do relatively well in *educational services*, black females in *health* and *social services*. Black men,

[19] The differences in industrial concentrations discussed here are generally significant statistically, due to the large sample sizes of the data.

Table 11: Distribution across selected major group industries in 1996-98 among complete and partial escapers by race/gender: for those with low earnings in base period

	White Female	White Male	Black Female	Black Male	Other Female	Other Male
Manufacturing	7.66	11.08	10.92	14.48	21.46	21.88
-Food etc	0.67	0.83	1.26	1.63	2.82	2.68
-Apparel	0.88	0.41	1.54	0.52	5.15	2.80
-Printing & publishing	1.19	1.23	1.11	1.29	0.93	0.99
-Electrical equip.	0.85	0.76	0.92	0.95	2.55	2.30
-Other	4.07	7.85	6.08	10.10	10.00	13.11
TCU	3.07	6.50	4.10	7.65	2.82	4.91
-Local passenger transit	0.52	1.02	1.42	1.59	0.44	0.45
-Motor freight transp.	0.70	2.74	0.43	2.84	0.36	1.83
-Transportation by air	0.60	0.84	0.77	1.59	0.60	0.74
-Transportation services	0.49	0.39	0.25	0.34	0.69	0.60
-Other TCU industries	0.76	1.51	1.23	1.29	0.73	1.29
Retail trade	24.75	21.74	17.02	18.31	20.68	22.20
-General merchandise stores	3.95	1.52	3.58	1.72	2.84	1.51
-Food stores	3.91	2.53	2.74	2.11	2.84	3.05
-Eating and drinking places	8.83	8.66	6.41	8.12	8.71	11.92
-Miscellaneous retail	3.68	2.51	1.57	1.55	2.71	1.56
-Other Retail trade industries	4.39	6.52	2.71	4.81	3.58	4.16
Services	50.39	34.44	56.61	38.93	42.29	28.39
-Hotels etc.	1.61	1.77	3.54	2.32	3.42	2.82
-Personal services	2.12	0.80	1.85	0.90	2.31	0.97
-Business services	6.19	10.39	10.24	15.64	7.55	9.96
-Health services	12.17	3.07	16.68	4.55	8.42	2.50
-Educational services	15.94	5.43	8.82	4.51	9.77	2.28
-Social services	4.09	1.59	9.80	3.74	4.11	1.12
-Other Services industries	8.27	11.40	5.67	7.26	6.71	8.74

more than any other group, sometimes manage to escape low earnings while still in the business services (i.e., temp agency) sector.

What accounts for the differential success rates in escaping low earnings that different race/gender groups enjoy across different industries? Few answers appear directly in these data, though some clues can be found in a broader range of literature. The declining presence of black men in manufacturing has been well noted, and is sometimes attributed to higher skill requirements there associated with new technologies; yet this can hardly account for why white and other (Hispanic) males who initially have low earnings can still do fairly well in this sector. The growing concentrations of remaining construction and manufacturing jobs in smaller/nonunion establishments, suburban areas, and smaller towns may help to explain this trend, to some extent.[20] Perhaps the relatively high-paying jobs as truck or bus drivers have experienced these changes to a much lesser extent and remain more accessible to black men. The good experiences that some black men have had with temp agencies has been documented by Young (2002). The relatively greater presence of black women in health services and social services, while white women are more heavily found in educational services, could reflect the long-term effects of employment contacts and networks established years ago, as well as the more recent choices of these workers.

These differences also raise major questions about the extent to which public and private labor market intermediaries (through job placement services, job developers and the like) should seek to reinforce these differences in mechanisms or "level the playing field", by improving the access of underrepresented groups to the same good jobs that do not require much skill. We return to this issue below.

Before concluding this section, we turn in Table 12 to the distributions of initially low earners across categories of firms based on size, job flow rates (i.e., net growth), churning (turnover), and firm wage premia. As before, we analyze job stayers and job changers separately, and also those who have or have not escaped low earnings status within each of these groups.

As expected, escape rates from low earnings status are higher in large firms, those with low turnover, and those with high wage premia. Somewhat interestingly:

[20] For evidence on the declining representation of black men in manufacturing jobs, and on the effects of growing suburbanization of these jobs see Bound and Holzer (1993), Kasarda (1995), Wilson (1996) and Holzer (1996). For descriptions of the growing presence of Hispanics in manufacturing, and of more favorable views of employers towards immigrants than African-Americans see Waldinger (1987) and **?**.

- *Larger firms are better places to escape poverty by staying but not by changing jobs*, perhaps reflecting the importance of having internal job ladders for the former process; and
- H*igh wage premia are more useful for those changing jobs than those staying in their previous ones*, perhaps indicating that those who start off with initially low earnings in any firm have more difficulty getting on a career ladder within high-wage firms than if they enter from the outside.

Overall, this section confirms that individuals who were persistently low earners during the base period of the earlier 1990's have often managed to at least partially escape this status in the later 1990's. Some groups – i.e., white males – escape their low earnings more frequently than others, especially blacks. Job and industry changing are frequently used as mechanisms for doing so, though those who stay on their earlier jobs can sometimes be successful as well – especially when these jobs are located in large firms and/or highly-paying sectors. Specific industry and firm characteristics often are associated with movements out of low earnings, though somewhat different pathways are taken by successful members of different demographic groups. Finally, we see that temp agencies play important roles in helping low earners transition to better jobs, especially those located in manufacturing and other traditional high-paying sectors in the economy.

4.3 Analysis of Stayers and Changers in Specific Jobs

The previous section provided evidence on transitions out of low-earnings status in successive 3-year periods. However, this analysis suffers from some limitations. For one thing, by focusing on the primary jobs within a 3-year period, we might miss some of the effects associated with shorter spells of employment. This framework is not suited for analyzing the important effects of *tenure*, through which improvements in wages for those staying on the same jobs are most likely to occur. The direct relationship of earnings, rather than annual incomes, to tenure and other characteristics of workers and jobs should be analyzed more directly by considering jobs on a quarter-by-quarter basis, looking at continuous measures of earnings levels and changes rather than discrete categories that are somewhat arbitrarily drawn.

In this section we once again consider jobs held during a base period before or during 1995 v. a subsequent period that begins in 1996. But instead of considering fixed 3-year blocks of time, we analyze the last job

Table 12: Distribution of workers across firm characteristics by job mobility and earnings transitions: for those with low earnings in base period

	Stayers			Job changers		
Limits of each	Still low	Partial	Complete	Still low	Partial	Complete
category	earnings	escapers	escapers	earnings	escapers	escapers
			Firm size*			
(0,20]	29.34	23.61	19.48	21.43	18.11	16.35
(20,50]	9.86	10.35	9.84	10.94	11.94	11.41
(50-100]	6.78	7.54	7.77	8.53	10.25	10.05
(100,500]	15.54	18.15	18.45	19.70	23.15	23.37
(500,∞)	38.48	40.34	44.46	39.39	36.56	38.82
			Job flow rate*			
Firm Exit	2.83	2.86	2.66	3.70	3.00	2.74
(-2, -1]	1.09	1.09	0.64	1.58	1.20	0.79
(-1,-0.5]	2.01	1.92	1.28	2.19	1.84	1.64
(-0.1,0.1)	14.08	13.97	11.93	14.92	13.14	13.00
(-.5,-0.1]	60.12	58.91	61.24	43.12	44.76	48.28
[0.1,0.5)	16.87	17.81	20.34	23.41	24.85	25.97
[0.5,1)	1.72	1.70	1.60	3.90	3.88	3.21
[1,2)	0.66	1.05	0.21	1.99	2.00	1.29
Firm Entry	1.58	1.67	0.27	5.18	5.34	3.08
			Worker churning rate*			
[0,0.1)	7.45	7.27	11.30	2.62	6.42	14.45
[0.1,0.2)	21.57	23.38	27.45	9.33	17.13	26.45
[0.2,0.5)	33.85	36.47	37.03	28.49	36.68	34.45
[0.5,1)	21.22	21.10	16.47	29.28	22.72	15.00
[1,2)	11.23	8.56	6.03	17.69	11.58	7.20
[2,∞)	4.68	3.21	1.72	12.60	5.47	2.45
			Firm wage premium*			
(-∞,-0.15)	72.49	62.32	40.27	69.83	39.28	20.30
[-0.15,0)	15.19	21.03	23.71	16.54	22.62	18.11
[0,0.15)	6.80	10.55	19.88	8.64	19.19	23.22
[0.15,∞)	5.52	6.10	16.15	4.99	18.91	38.38

* Defined in text to Table 4

Table 13: Mean quarterly real earnings

	Low-earners*		Non-low earners*	
	Base period**	Subsequent period**	Base period**	Subsequent period**
	Job changers***			
All	1,180	1,641	4,147	4,544
White-Female	1,108	1,574	3,747	3,996
White-Male	1,294	1,967	5,007	5,551
Black-Female	1,137	1,567	3,100	3,221
Black-Male	1,194	1,630	3,403	3,654
Other-Female	1,158	1,518	3,369	3,691
Other-Male	1,240	1,618	3,944	4,468
	Job stayers***			
All	1,177	1,348	4,868	5,181
White-Female	1,096	1,298	4,246	4,528
White-Male	1,262	1,439	5,951	6,317
Black-Female	1,140	1,293	3,630	3,865
Black-Male	1,292	1,468	4,234	4,520
Other-Female	1,167	1,297	3,875	4,133
Other-Male	1,327	1,463	4,600	4,925

* Low earnings if real (deflated by CPI-U) annual earnings are below $12,000 (in 1998 U.S. dollars) in each year in 1993-95; else non-low earnings

** Earnings in base period reflect average full-quarter earnings in 1995 and prior at the last full-quarter job held in 1995; earnings in subsequent period reflect average full-quarter earnings in 1996 and onwards at the first full-quarter job held in 1996.

*** If first full-quarter employer in 1996 is different from last full-quarter employer in 1995, then the individual is defined as a job changer; else the individual is a job stayer.

Table 14: Changes in log earnings for individuals with low earnings in base period

	Mean	p25	p50	p75	Mean	p25	p50	p75
	Job changers				Job Stayers			
Difference in average full-quarter log earnings in subsequent period and average full-quarter log earnings in base period								
All	0.30	-0.11	0.24	0.68	0.10	-0.08	0.07	0.26
White-Female	0.33	-0.08	0.28	0.71	0.12	-0.07	0.08	0.28
White-Male	0.40	-0.04	0.32	0.83	0.09	-0.10	0.07	0.26
Black-Female	0.24	-0.11	0.20	0.59	0.09	-0.07	0.06	0.25
Black-Male	0.26	-0.10	0.24	0.64	0.08	-0.11	0.04	0.23
Other-Female	0.24	-0.14	0.18	0.59	0.08	-0.08	0.07	0.26
Other-Male	0.24	-0.14	0.22	0.62	0.06	-0.08	0.06	0.23
Difference between first full-quarter log earnings in subsequent period and last full-quarter log earnings in base period								
Total	0.27	-0.14	0.21	0.67	0.07	-0.15	0.01	0.19
White-Female	0.28	-0.17	0.19	0.67	0.11	-0.13	0.09	0.32
White-Male	0.36	-0.10	0.29	0.80	0.00	-0.17	0.01	0.13
Black-Female	0.20	-0.17	0.19	0.61	0.19	-0.07	0.09	0.32
Black-Male	0.23	-0.17	0.20	0.58	-0.01	-0.19	-0.01	0.16
Other-Female	0.25	-0.13	0.16	0.68	-0.01	-0.16	0.01	0.18
Other-Male	0.22	-0.16	0.16	0.65	0.00	-0.16	0.01	0.12

Table 15: Mean full-quarter tenure

	Low-earners		Non-low earners	
	Base period	Subsequent period	Base period	Subsequent period
	Job changers			
All	5.71	4.84	7.93	6.62
White-Female	6.25	5.25	7.98	6.68
White-Male	5.29	4.45	8.00	6.67
Black-Female	5.36	4.77	7.90	6.48
Black-Male	4.77	3.87	7.51	6.03
Other-Female	5.85	5.04	7.94	6.64
Other-Male	5.38	4.62	7.77	6.65
	Job stayers			
All	8.13	14.92	10.45	19.29
White-Female	8.76	16.03	10.55	19.38
White-Male	7.57	13.73	10.48	19.40
Black-Female	7.89	14.57	10.46	19.27
Black-Male	6.63	12.07	10.23	18.76
Other-Female	8.28	15.39	10.44	19.27
Other-Male	7.13	13.16	10.15	18.91

Table 16: Mean of firm wage premium

	Low-earners		Non-low earners	
	Base period	Subsequent period	Base period	Subsequent period
		Job changers		
All	-0.32	-0.23	0.07	0.07
White-Female	-0.33	-0.25	0.05	0.04
White-Male	-0.35	-0.20	0.10	0.11
Black-Female	-0.26	-0.19	0.06	0.05
Black-Male	-0.33	-0.25	0.05	0.04
Other-Female	-0.29	-0.22	0.05	0.05
Other-Male	-0.35	-0.27	0.05	0.06
		Job stayers		
All	-0.33	-0.33	0.07	0.07
White-Female	-0.33	-0.33	0.03	0.03
White-Male	-0.38	-0.38	0.11	0.11
Black-Female	-0.26	-0.26	0.09	0.09
Black-Male	-0.39	-0.39	0.10	0.10
Other-Female	-0.28	-0.28	0.06	0.06
Other-Male	-0.34	-0.34	0.07	0.07

Note: that the two first and two last columns in the lower panel are the same by construction, since the firm has not changed and the wage premium is a fixed characteristics of the firm.

held during the base period and the first one held subsequent to that one. If the two jobs are the same, the person is considered a job-stayer; if they are different, (s)he is a job-changer, as noted above.

In Table 13 we present summary data on quarterly earnings among those holding jobs during the base period and afterwards, separately for job-changers and stayers. To maintain continuity with the earlier analysis, and to provide ex-ante measures of low earnings status that are themselves not dependent on any labor market outcomes that occur subsequently, we use the same definitions as before to categorize workers as initially low earners or non-low earners – i.e., whether or not they earned less than $12,000 a year for each of the 3 years during the base period.[21][22] We also provide results for all workers and then for subgroups by race/gender.

The results of Table 13 indicate that low earners were paid approximately $1,200 per quarter during the base period, while non-low-earners were paid an average of just over $4,000 initially. Job stayers earned significantly more than job changers among non-low earners, indicating some non-random selection into these different job mobility groups; while the base period earnings of low earners are comparable across stayers and changers.

Furthermore, all groups of workers enjoyed higher quarterly earnings in the subsequent period than in the base period. Average earnings among all job-stayers grew by about 6% for non-low earners across the two periods and by nearly 15% for low earners. But, among both groups, job changers improved their earnings by more than job stayers; and this difference is particularly pronounced among the initially low earners. In fact, earnings grew by 10% for non-low earning job changers and *by 39% for low-earning job changers across these two periods*. And, considering the results separately by race and gender, we note again that white males earn considerably more than other groups among non-low-earners and among low earners in the subsequent period, but not among low earners initially; these results imply that *low-earning white males gained more from changing jobs than any other race/gender group*.

Of course, job changing does not always generate significant improve-

[21] In this section, we limit the sample of low earners in the base period to those who were in the persistent low earnings category during the entire base period. In other words, those with "partially low" or "partially non-low" earnings are included with the non-low earners.

[22] Of course, this definition implies that the earnings during the base period (as opposed to the subsequent period) will be heavily affected by this sampling definition, and that the sample itself is partly drawn on the basis of outcome measures. We discuss this issue further below.

ments in earnings, as we noted in the earlier section; and it is well-known that involuntary job changes (especially job displacements) are often associated with major wage losses (e.g. Holzer and Lalonde, 2000). Thus, the mean wage increases implied by Table 13 might mask considerable variation in wage increases within each of the groups considered.

In Table 14 we present data on the distribution of real wage increases for job changers v. stayers who had low earnings during the 3-year base period. The increases are now measured as changes in log quarterly earnings, so magnitudes differ slightly from those implied in Table 13. The changes are also measured two ways: as the differences in earnings averaged over all quarters in the base and subsequent periods; and also as the difference between the first full quarter of the subsequent period v. the last full quarter of the base period, thus avoiding tenure effects in both measures.

The results of Table 14 indicate that mean and median wage increases are again much larger for job changers than job stayers; and increases for white males exceed those of all other groups while those of blacks lag behind. But wage increases at the 25th percentile are much more negative among job changers than stayers, again indicating the greater downward as well as upward potential associated with job changes. On the other hand, the gains at the 75th percentile are very high among the job-changers.

In Tables 15 and 16 we consider summary data on two more characteristics of workers and their jobs, separately for the initially low earners and non-low earners in the base and subsequent periods, for all workers and by race/gender. In Table 15, we consider data on quarters of job tenure acquired by workers; while in Table 16 we present data on the firm wage premia.

The results of Table 15 indicate that non-low earners accumulate more job tenure than do low earners, which might well to contribute to the higher earnings of the latter than the former. It is also clear that job stayers accumulate more tenure in the subsequent period than do job changers, which is clearly a direct consequence of staying on the job. Thus, at least part of the relatively larger wage gains experienced by job changers is offset by higher tenure of the stayers - assuming that such tenure is rewarded in their jobs.

The tenure of job changers in the subsequent period lags behind that of the base period, because outcomes in the subsequent period are more likely to be truncated by the end of the sampling period. This is true for changers in both the non-low and low earnings categories. It is also unclear from these data whether or not low earners react somewhat to improved job opportunities with longer relative tenures on the subsequent job after they change jobs and improve their earnings.[23]

We also note that higher job tenure is *not* a major source of the generally higher wages earned by white males relative to other groups that we observed in Table 13. Among non-low earners, the tenure of white males and females is quite comparable, while among low earners the measure is generally higher for white females. Indeed, the tendency of females to have higher tenure than males is observed within all race groups and virtually all groups of earners. On the other hand, the tenure of blacks and other workers tend to lag a bit behind those of whites, and the low tenure earned by black males among low earners is especially noteworthy.

The data on firm wage premia in Table 16 indicate that the firms in which non-low earners work pay considerably higher wages than those of low earners, which no doubt contributes to the observed differences in earnings between the two groups. The firm premia stay constant among job-stayers (by definition) and also among non-low earning job-changers. However, there is a noteworthy improvement in firm wage premia among low-earning job-changers - with a 9-log point increase in that average premium. Indeed, the gap in job quality between low and non-low earners decreases from 39 to 30 points, or by nearly a fourth. This will likely help to account for some of the higher wage growth experienced by low earners, as we will see below. And the gain in the firm wage premium for white males among the low-earners (15 log points) is again considerably higher than that for any other race/gender group among them, no doubt contributing to their relatively greater wage gains as well.

To analyze the net effects of these various person and firm characteristics on the wage gains of initial low-earners across these two periods, we present results from several regressions in Tables 17 through Table 19.[24] The regressions take the standard form of a log earnings equation:

$$\ln(Earn)_{ijt} = a + bX_i + cX_j + dX_{it} + fX_{jt} + gX_{ijt} + u_{ijt} \tag{1}$$

where $Earn_{it}$ represents the quarterly earnings of person i in firm j in quarter t; and the X represent characteristics of the person and/or job. Thus the X_i and X_j represent time-invariant characteristics of each - such as the fixed wage premia of the person and firm respectively, as well as the

[23] The tenure gap (between low and non-low earners) rises over time among the job-stayers and declines over time among the job-changers in absolute terms, but not percentage terms in Table 12. Whether or not the gap would narrow if the subsequent jobs among the job-changers were less heavily truncated by the ending of the sample period cannot be ascertained.

[24] Comparable results for non-low earners are available as well for comparison purposes.

worker's race and gender and the firm's industry; the X_{it} and X_{jt} represent time-varying characteristics of each, such as experience for the former and size/turnover/job flows for the latter; and the X_{ijt} represent time-varying characteristics of the match between the two – most notably, job tenure.[25]

The equations are estimated across person-quarters for each of the relevant samples. In Table 17, we present results for initial low earners who are job-stayers, while in Table 18 and Table19 we present results those who are job-changers. The latter are presented separately in their base period and subsequent jobs respectively in parts a and b of the table. Of course, the sample of low-earners during the *base period* (but not the subsequent period) is drawn on the basis of the outcome variable, which implies that estimates for that period could be heavily biased relative to the true parameters for the full population of low-earners (which would also include transitory low earners that are, by definition, excluded from this sample). However, the results accurately reflect the effects of person and job characteristics on earnings *for this particular sample*, and therefore can be used for comparison purposes with the fully unbiased results on subsequent jobs for the same set of workers.[26]

For each set of regressions, four specifications are presented, including: 1) the fixed and time-varying characteristics of the individuals, such as race/gender, experience and experience-squared, and the fixed wage pre-

[25] No time dummies (i.e., X_t) were included in these equations, as they are quite highly correlated with measured job tenure. Thus, it is very difficult to sort out the effects of tight labor markets and other aggregate effects over time in these results. But all equations include state dummies in addition to the independent variables listed in the text. Separate estimates of all of these results by state indicate broadly similar patterns of results and are available upon request.

[26] Even the regression estimates for initially low-earning job-stayers might be somewhat biased by the requirement that individuals in the sample had to have low earnings for three consecutive years. However, the biases should be less severe in this case, as that requirement is lifted for all quarters beyond the base period. Since the job held in this sample is the same in the base and subsequent periods, and tenure is measured in that job across the two periods, we present a single set of estimates for initially low-earning job stayers across both periods. However, we have estimated separate equations for the base and subsequent period as well for this group, and the unbiased results for the subsequent period are qualitatively similar to the ones described below.

mium for that person;[27] 2) tenure and tenure-squared are added;[28] 3) the firm wage premium is added, as the single best measure of firm effects on wages; and 4) other fixed and time-varying characteristics of the firm are added. In addition, the equations for job changers (Table 18 and Table19) include two additional specifications – one that adds a dummy variable to equation 2) for whether or not the worker was employed by a temp agency in the base period, and one that adds this dummy to equation 4). Though no controls for education or cognitive skills are included directly in these equations, the inclusion of person-specific fixed effects likely controls for these important personal characteristics.

Overall, the results of Tables 17 through 19 are largely as expected. White males generally earn more than females and/or minorities (though not in each case in every subsample); returns to general experience and tenure with an employer are usually positive and sometimes show the expected diminishing returns; and both fixed personal and firm effects have positive effects on individual earnings. The addition of industry, size, and other characteristics to the equations show some significant effects even after controlling for fixed firm effects, though their effects are much stronger without including the latter control.[29] The addition of the full range of firm characteristics to these equations usually accounts for an additional 20 percent or so of the variance in earnings explained in these equations (as measured by the R-squared).

It is noteworthy that returns to virtually all of these characteristics are highest for job-changers in their new jobs. Thus, the new jobs into which job-changers move reward personal characteristics more fully, and the characteristics of the firms themselves matter more as well. Of course, these higher returns can imply higher or lower net wages, depending on the exact characteristics of the person and the job.

[27] Since person and firm fixed effects have been estimated on a full sample of workers outside of this sample, we can include other fixed characteristics of the person (such as race and gender) and of the firm (such as industry) along with these fixed effects in any equations estimated with this sample. But the estimated effects of race/gender as well as industry must then be interpreted as those that go beyond the fixed wage characteristics of the workers and firms in question.

[28] The squared terms represent the quadratic functional form for experience and tenure, which is commonly used in the estimation of log earnings equations.

[29] The rationale for including industry and other variables even after controlling for the firm wage premium is that the former might capture differences across firms in benefits or in wage inequality that that the latter misses. Details on which of these measures have significant effects on wages, either with or without the controls included for the firm wage premium, are available from the authors.

The size of the coefficient on the firm fixed effect is also worth discussion. In particular, in Table 17 and Table 18, the coefficient for stayers is about .654, while for changers it is .868. Since the coefficient for the full sample, without restrictions, is 1, this can be interpreted as the degree to which this subset of workers is able to capture wage premia from the firms for which they work.

One characteristic which is clearly rewarded more heavily after job changes is tenure on the job. Figure 1 plots out the returns to job tenure for job-stayers and job-changers, before and after the latter move.[30] The results are quite striking:

- *For initially low-income workers, returns to tenure are positive but modest for job-stayers*, averaging about 1-2 log points per year in real terms;

- *Returns to tenure for job-changers are mildly negative on their early jobs but very strongly positive in their new ones.* Indeed, these returns imply earnings increases of nearly 20 points over the first year and about 30 points over the first two years.

The very weak returns to tenure in the base period imply that many of these jobs were truly "dead-end", and generated a strong incentive to change jobs, while the much higher returns afterwards suggest strong incentives to remain with these newer firms. Table 15 indicates, in fact, that tenure improves somewhat for low-earning job-changers (relative to others) on their new jobs, though the full extent of any such improvement is difficult to measure here (because of the right-side truncation of the data noted above).

Do these returns to tenure differ significantly across demographic groups or jobs? We have calculated separate returns to tenure by race/gender group and by industry and firm size among those with initially low earnings. Our results indicate that men generally enjoy higher returns than women, and that a few industries (such as construction) generate higher returns than most others.[31] But otherwise there is no strong or consistent pattern to these returns, and they seem to account for little of the differences in average tenure across groups that we observed in Table 15. Given the literature on

[30] We use coefficients from equation 2) to generate these graphs.

[31] Details on these estimates are available from the authors. We find no evidence of lower returns to tenure for blacks than whites, even though they have lower mean tenure on average. This is consistent with a higher rate of involuntary terminations among blacks than whites, as found by Ferguson and Filer (1986) and also Jackson and Montgomery (1986).

determinants of job turnover that we mentioned earlier (e.g. Holzer and Lalonde, 2000), this is perhaps not very surprising – as many characteristics of individuals enter into their decisions to stay/leave their jobs and their employers' decisions to retain/discharge them.

The addition of firm characteristics to these equations in columns 3) and 4) of Table 17 illustrate another point:

- *Firm characteristics account for 30-40% of the earnings gaps of black males, and about 35-45% of the gaps of other males, relative to white males subsequent to a job change.*

Thus, job characteristics help to account for a good portion of observed earnings differences among these men, but much less of the differences between men and women within racial groups.

Another important finding emerges from Table 17 and Table 18 with regards to temp agencies:

- *Those low earners who worked with temp agencies in the base period and who then changed jobs earn about 8 log points more on their subsequent jobs than do others, while they were earning 9 log points less while working at the agencies;* and

- *Both of these differentials are almost fully accounted for by the characteristics of the jobs in each case*, since both effects effectively disappear when job characteristics are added to the model.

Even more than the earlier results, these conclusively show that temp agencies help place low earners into better subsequent jobs, even though the earnings they receive while working for the agencies are somewhat meager. Whether this implies that a broader range of low-income workers could benefit from the services of temp agencies, or from other labor market intermediaries, is harder to claim, since it is possible that those most likely to benefit have already been selected (by themselves, welfare-to-work administrators, or others) into these agencies. We discuss this more fully below; but, in the meantime, the fact that temps generate positive subsequent effects for the low-income workers whom they currently employ is important for the debate on these agencies that is currently raging.

Finally, what do these regression results imply about our ability to explain the very strong improvement in average earnings enjoyed by job-changers who initially had very low earnings? To answer this question, we decomposed the earnings gains for job-changers using the well-known

Blinder-Oaxaca decomposition, in which overall changes in the means of the dependent variable are attributed either to changes in the means of independent variables or to changes in estimated parameters.

Overall, *both the improvement in returns to experience and tenure, as well as the characteristics of the jobs attained account for major portions of this overall wage gain* - though a fairly large portion of the improvement is also unexplained by these equations.[32] Interestingly, the firm characteristics that matter most are the *levels* of wages in firms and on these jobs, while returns to tenure represent *changes* in these levels over time. Thus, both the current levels of earnings and their potential for improvement are important determinants of successful job changes for those with initial low earnings.

Before concluding, we return to an issue noted earlier – namely that changing jobs entails some costs as well as gains. Tenure is clearly reduced substantially by those who change jobs, and even wages are reduced for a significant fraction of those changing jobs. In addition, those who change jobs clearly lose some earnings because of lost employment time in between jobs.

Are these losses substantial? Table 19 presents data on quarters of lost employment time for the initial low earners who change jobs.[33] The results are also presented separately for "winners" and "losers" in terms of earnings – i.e., for those with significant earnings increases after the job change v. those without such gains – since the former are more likely to be changing jobs voluntarily and therefore might suffer a shorter spell without employment between jobs. [34]

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[32] The decomposition attributes the change in mean of log earnings for job changers with low earnings in the base period to changes in mean characteristics of the individuals and changes in returns to these characteristics between the two periods. The results from this decomposition are that: 5 percent of the overall change in mean log earnings can be attributed to changes in the mean of fixed individual characteristics between the two periods; similarly, changes in the mean of fixed firm characteristics, experience and tenure accounts for 25, 10 and 3 percent, respectively. Changes in the returns to fixed individual characteristics, fixed firm characteristics, experience and tenure accounts for –33, -27, 52 and 46 percent respectively. These numbers together with the fraction of change that can be attributed to the change in constants between the two periods, which accounts for 21 percent and which can be interpreted as the fraction of change that cannot be accounted for by observable factors, add up to 100 percent.

[33] Lost employment time is defined as the sum of full quarters of non-employment between job in base period and job in subsequent period and the estimated fraction of non-employment in the first quarter at new jobs and in the last quarter at old job. Fraction of quarter non-employed in first and last quarter is estimated by comparing income levels in those quarters with adjacent quarters.

[34] The percentage of job changers among initial low earners who fit the definition of

The results indicate that the losses in employment time are not insubstantial – the median time spent out of work is 3 quarters and the mean about 4 quarters, with no obvious pattern across race/gender groups. Lost employment time is somewhat higher (about 9%) for earnings losers than for winners, though the differences here are not dramatic. Either way, the loss of employment time is quite high relative to durations of unemployment/nonemployment that are usually observed for more typical samples of workers.[35]

Of course, lost employment time likely reflects certain job search or labor force choices among the nonemployed as well as the direct consequences of the decision to leave the previous job. Some of this loss might thus be the choice of the workers themselves. Nevertheless, when factored in along with losses in observed wages for some of these workers, it is clear that job change does not generate earnings improvements universally, and should not be viewed as a panacea for low earnings in the market. Instead, it can be viewed as a successful strategy for many (though not all) of those who select to take it, particularly those who have access to subsequent jobs that are better than their previous ones.

5 Conclusions

In this paper, we have analyzed the earnings of persistently low earners, and how they change over time. In particular, we analyze long-term patterns of earnings growth and transitions out of low-earning status. We focus particularly on the role played by firm characteristics, such as industry, firm size, firm wage premia, and other measures that represent the quality of jobs and firms to which low earners have access. We do this analysis using the LEHD data from the U.S. Census Bureau, which will ultimately combine the universe of UI wage records for each state with data from the household and economic censuses.

Overall, the main results of this analysis are as follows:

- A significant fraction (about 12%) of prime-age adults in the United States with regular labor force attachment have very low earnings (i.e.,

being an earnings "loser" here is 35%.

[35] Part of the reason for the apparently long jobless durations here is that we focus on the non-employed rather than the unemployed, where the former can include people who spend some each year out of the labor force. Also, even by this definition, lost employment time for initial low-earners is more than twice as high as that for non-low earners in our sample. For more evidence on lengthy non-employment spells among minorities or low-wage workers see Clark and Summers (1982) or Juhn, Murphy, and Topel (1991).

$12,000 per year or less) that persist over a period of at least three years;

- These low earnings are associated both with their own demographic characteristics (i.e., race/gender and where they were born) and many characteristics of the firms for which they work (i.e., industry, size, turnover and net employment growth rates, and firm wage premia);
- Of those with persistently low earnings, nearly half manage to escape this status in subsequent years, though earnings improve only partially for most of them (i.e., they continue to earn less than $15,000 in at least some years);
- Of those with persistently low earnings, white males enjoy the highest subsequent earnings gains and highest rates of "escape" from this status of any race/gender group, while blacks endure the lowest improvements;
- Job and industry changes are associated with large percentages of the observed improvements in earnings, though a significant fraction (i.e., roughly a fourth to a third) of all escapes from low-earning status also occur among those who stay on initial jobs;
- Most earnings improvements for low-earning women occur within the service sector – in areas such as financial services, health care and education - while a larger fraction of gains for males occur in the "traditional industries" like construction, manufacturing, transportation and wholesale trade;
- Significant parts of the lower subsequent earnings of black and other (mostly Hispanic) males among initial lower earners are accounted for by their lesser access than white men to high-quality jobs;
- Improvements in earnings associated with successful job changes for these workers are largely due to improvements in the returns to experience and job tenure associated with the new jobs, and also to the better characteristics of the new firms for which they work – i.e., improvements in both the current levels of earnings and their rates of improvement over time; and
- Temp agencies are associated with lower pay for low earners while they work for them but higher subsequent wages and better job characteristics afterwards.

These findings have some important implications for the low-wage labor market. For one thing, *some degree of upward mobility for persistently low earners is certainly possible*, and in fact is being achieved – even if these improvements remain fairly modest in most cases. Also, there is *no single path* for achieving earnings growth. Job changes are important to many who achieve earnings improvements, though staying on the job also works in a significant percentage of cases. What matters most is not job mobility *per se* but whether or not the individual ends up in a good job, either with or without an intervening job change.

A range of characteristics also seems to be associated with these good jobs – including not only firm wage premia (which are not observable to workers or labor market practitioners) but also industry, firm size, rates of turnover and employment growth (which are observable). Thus, it is useful to try placing low earners into high-wage sectors, firms with low turnover, and larger firms that provide job ladders and possibilities of upward mobility.

The fairly positive results observed here for low earners who have worked with temp agencies might also lead us to suggest that more workers should work with such agencies, or at least with some type of labor market intermediary organization. Of course, any such recommendation is subject to the strong caveat that these agencies may work for some but not for others, and that those for whom they are successful may already be self-selecting into them. On the other hand, the results here do provide some useful labor market information for intermediaries that are working with low earners, and they are supportive of the ongoing efforts of temp agencies with their current workforces.

The results also suggest a strong need to improve access to good jobs for many low earners – especially those who are not white males. Unfortunately, this analysis provides no direct evidence on what limits access for to such jobs for many groups. On the other hand, a wide literature already exists on the barriers that minority and especially blacks face to gaining better jobs. These barriers include employer discrimination (especially at smaller establishments and those with lots of white customers); "spatial mismatch" associated with poor transportation to or information about suburban job openings for those in inner-city areas; weak employment networks and early work experience; etc. (Holzer, 1996; Holzer, 2000). The results here do suggest that efforts by laboar market intermediaries and other policymakers to reduce these barriers and improve access to better jobs for blacks could bear important fruit in labor market outcomes for these low-earning groups.

The analysis presented above suffers from a variety of limitations as well. As noted, potential selection issues limit the extent to which we can advocate any particular labor market path for those not already taking it. Many important characteristics of workers here are not observable – most notably measure of skill, such as education and cognitive sills. While these attributes are likely captured in the worker fixed effects for which we control, it would be useful to have more direct measures of them. On the other hand, many of our observed differences across groups in labor market outcomes can be found even after controlling for person fixed effects; and differences between white males and females, or between blacks and other minorities (especially Hispanics), certainly cannot be attributed to omitted skill measures.[36]

Having data on educational outcomes, hourly wages, and family/household structure (such as spouse's earnings and presence of young children) would certainly help us distinguish between the persistently low earners who might choose such a status voluntarily, as opposed to those who face very constrained opportunities in the labor market. Therefore, an important item on our future work agenda is to more fully integrate these data and other household surveys, such as the PUMS data of the Census and the CPS, to focus more clearly on groups that are really poor. This analysis will also indicate the extent to which we can rely on administrative data alone (for example, from UI wage records) for making these inferences, rather than on linked administrative-survey data which are harder to develop.

[36] Neal and Johnson (1996) attribute much of the lower earnings of blacks relative to whites to the lower education and test scores of the former. But this explanation cannot account for lower earnings or success in escape among blacks than Hispanics, who generally have lower educational attainment and lower test scores than blacks. It also cannot explain differences between males and females within each racial group.

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Appendix

Table 17: Regressions of log quarterly real earnings: job stayers with low earnings in base period, using data from both periods.

	(1)	(2)	(3)	(4)
White Women	-0.088	-0.09	-0.152	-0.145
	(13.55)**	(13.92)**	(26.27)**	(24.57)**
Black Women	-0.024	-0.026	-0.142	-0.140
	(2.61)**	(2.90)**	(17.29)**	(16.76)**
Black Men	0.078	0.081	0.072	0.057
	(6.62)**	(6.94)**	(6.83)**	(5.43)**
Other Women	-0.039	-0.041	-0.116	-0.122
	(5.05)**	(5.32)**	(16.88)**	(17.53)**
Other Men	0.077	0.077	0.031	0.023
	(9.10)**	(9.17)**	(4.12)**	(2.97)**
Fixed person wage premium	0.383	0.376	0.587	0.585
	(99.52)**	(97.50)**	(151.79)**	(150.36)**
Experience	0.008	0.007	0.012	0.012
	(22.79)**	(21.45)**	(39.64)**	(40.46)**
Experience2/100	-0.002	-0.002	-0.003	-0.003
	(9.99)**	(9.97)**	(17.08)**	(17.52)**
Tenure		0.004	0.002	0.002
		(3.08)**	(1.71)	(1.94)
Tenure2/100		0.012	0.016	0.017
		(2.18)*	(3.23)**	(3.44)**
Firm wage premium			0.654	0.644
			(121.26)**	(110.01)**
Additional firm characteristics	No	No	No	Yes
Constant	6.855	6.828	6.957	6.864
	(496.89)**	(466.55)**	(529.09)**	(456.61)**
Observations	59,543	59,543	59,535	59,321
R-squared	0.15	0.16	0.33	0.34

All specifications include State dummies. Absolute value of t statistics in parentheses. * significant at 5%; ** significant at 1%.

*** The additional firm characteristics controls that are suppressed in the table include 10 dummies for industry, 9 dummies for different job flow categories, 6 dummies for different worker churning categories.

Table 18: Regressions of log quarterly real earnings in subsequent period: job changers with low earnings in base period

	(1)	(2)	(3)	(4)	(5)	(6)
White Women	-0.262	-0.268	-0.235	-0.237	-0.266	-0.237
	(23.76)**	(24.57)**	(25.44)**	(25.11)**	(24.31)**	(25.12)**
Black Women	-0.217	-0.222	-0.251	-0.26	-0.226	-0.26
	(14.63)**	(15.12)**	(20.19)**	(20.54)**	(15.38)**	(20.47)**
Other Women	-0.272	-0.277	-0.261	-0.258	-0.276	-0.258
	(20.67)**	(21.27)**	(23.63)**	(23.01)**	(21.18)**	(23.03)**
Black Men	-0.107	-0.105	-0.064	-0.072	-0.11	-0.072
	(6.00)**	(5.92)**	(4.24)**	(4.78)**	(6.19)**	(4.73)**
Other Men	-0.155	-0.158	-0.099	-0.088	-0.156	-0.088
	(11.49)**	(11.85)**	(8.77)**	(7.55)**	(11.69)**	(7.57)**
Fixed person	0.536	0.518	0.595	0.593	0.518	0.593
wage premium	(67.42)**	(65.40)**	(88.19)**	(87.93)**	(65.48)**	(87.92)**
Experience	0.01	0.009	0.012	0.012	0.009	0.012
	(18.41)**	(16.65)**	(24.52)**	(24.96)**	(16.72)**	(24.95)**
Experince2/100	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(8.85)**	(8.01)**	(11.11)**	(11.61)**	(8.09)**	(11.60)**
Tenure		0.056	0.043	0.044	0.056	0.044
		(12.69)**	(11.48)**	(11.75)**	(12.73)**	(11.75)**
Tenure2/100		-0.22	-0.165	-0.171	-0.22	-0.171
		(6.95)**	(6.15)**	(6.38)**	(6.97)**	(6.38)**
Firm wage			0.868	0.846		0.846
premium			(100.56)**	(85.71)**		(85.71)**
Temp industry					0.078	-0.011
in base period					(5.47)**	-0.93
Additional firm	No	No	No	Yes	No	Yes
characteristics						
Constant	7.218	7.048	7.154	7.146	7.041	7.147
	(324.91)**	(287.07)**	(343.47)**	(294.12)**	(286.43)**	(293.90)**
Observations	25,638	25,638	25,607	25,487	25,638	25,487
R-squared	0.17	0.19	0.42	0.43	0.19	0.43

All specifications include State dummies. Absolute value of t statistics in parentheses. *significant at 5%; **significant at 1%.

The additional firm characteristics controls that are suppressed in the table include 10 dummies for industry, 9 dummies for different job flow categories, 6 dummies for different worker churning categories.

Table 19: Regressions of log quarterly real earnings in base period: job changers with low earnings in base period

	(1)	(2)	(3)	(4)	(5)	(6)
White Women	-0.116	-0.112	-0.130	-0.122	-0.115	-0.122
	(15.43)**	(14.96)**	(18.31)**	(17.04)**	(15.28)**	(17.04)**
Black Women	-0.054	-0.052	-0.091	-0.083	-0.052	-0.083
	(5.20)**	(5.10)**	(9.33)**	(8.48)**	(5.03)**	(8.49)**
Other Women	-0.022	-0.020	-0.047	-0.059	-0.022	-0.059
	(2.44)*	(2.23)*	(5.62)**	(6.94)**	(2.47)*	(6.96)**
Black Men	0.013	0.011	0.015	0.014	0.015	0.014
	(1.11)	(0.93)	(1.39)	(1.34)	(1.34)	(1.32)
Other Men	0.037	0.036	0.033	0.020	0.034	0.020
	(4.05)**	(4.04)**	(3.83)**	(2.24)*	(3.79)**	(2.23)*
Fixed person	0.253	0.255	0.347	0.344	0.255	0.343
wage premium	(49.22)**	(49.54)**	(69.04)**	(68.79)**	(49.58)**	(68.76)**
Experience	0.005	0.005	0.007	0.007	0.005	0.007
	(12.08)**	(12.63)**	(19.48)**	(19.90)**	(12.80)**	(19.91)**
Experince2/100	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(3.58)**	(3.82)**	(6.51)**	(6.81)**	(3.96)**	(6.83)**
Tenure		-0.020	-0.014	-0.012	-0.021	-0.012
		(4.87)**	(3.49)**	(3.20)**	(5.09)**	(3.20)**
Tenure2/100		0.094	0.070	0.065	0.096	0.064
		(2.76)**	(2.19)*	(2.04)*	(2.84)**	(2.03)*
Firm wage			0.496	0.524		0.524
premium			(71.28)**	(69.07)**		(69.01)**
Temp industry					-0.090	-0.015
in base period					(8.04)**	-0.97
Additional firm characteristics	No	No	No	Yes	No	Yes
Constant	6.809	6.864	6.955	6.962	6.871	6.961
	(488.90)**	(408.75)**	(436.98)**	(379.79)**	(409.00)**	(379.74)**
Observations	41,772	41,772	41,710	41,519	41,772	41,519
R-squared	0.07	0.07	0.17	0.19	0.07	0.19

All specifications include State dummies. Absolute value of t statistics in parentheses. *significant at 5%; **significant at 1%.

The additional firm characteristics controls that are suppressed in the table include 10 dummies for industry, 9 dummies for different job flow categories, 6 dummies for different worker churning categories.

Table 20: Distribution of lost employment time: job changers with low earnings in base period

	Mean	P25	P50	P75
		"Winners"*		
White-Female	3.60	1.10	2.67	5.00
White-Male	3.99	1.38	3.00	5.00
Black-Female	3.68	1.37	3.00	4.89
Black-Male	3.59	1.62	3.00	4.70
Other-Female	3.86	1.61	3.00	5.43
Other-Male	3.57	1.47	3.00	4.85
Total	3.71	1.30	3.00	4.97
		"Losers"*		
White-Female	4.09	1.67	3.09	5.36
White-Male	4.20	2.00	3.41	5.07
Black-Female	3.77	1.64	3.00	4.90
Black-Male	3.85	2.00	3.26	4.79
Other-Female	4.31	2.00	3.33	5.66
Other-Male	3.70	2.05	3.11	4.34
Total	4.03	1.93	3.15	5.00

Note: Lost employment time is defined as the sum of full quarters of non-employment between job in base period and job in subsequent period and the estimated fraction of quarter employed in first quarter at new jobs and last quarter at old job. Fraction of quarter employed in first and last quarter is estimated by comparing income levels in those quarters with adjacent quarters. * "Winners" are those individuals whose earnings in the first full quarter at the new job are higher than earnings in the last full quarter at the old job. Correspondingly, "losers" are those whose earnings are lower in the first full quarter at the new job as compared to earnings in the last full quarter at the old job.

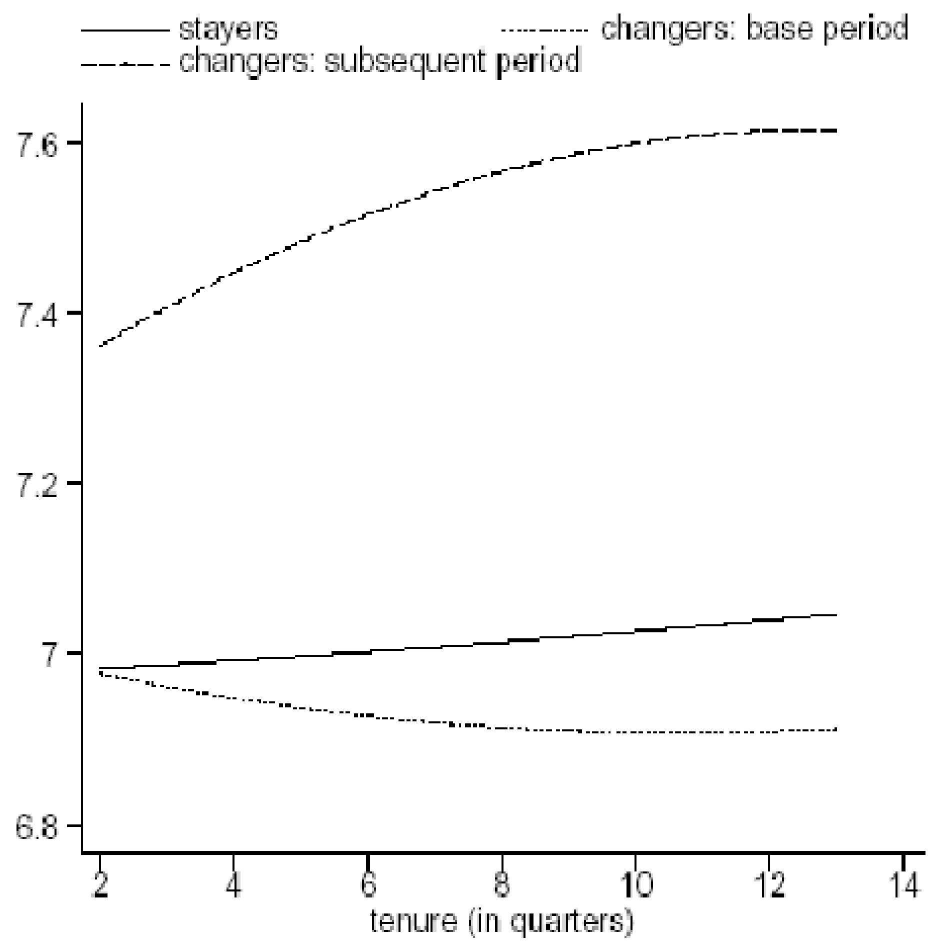

Figure 1: Wage-tenure profile: workers with low earnings in base period

Table A-1: Sample selection

	Observations	Individuals	Employers
Universe	854,593,228	57,823,057	2,913,197
Universe after age restriction	584,203,034	34,961,141	1,971,817
Universe after imposing labor force restriction	633,917,471	25,808,095	1,642,074
Universe after imposing labor force and age restriction	469,787,547	18,783,475	1,202,096
Total number in 5% sample		938,226	350,478

Table A-2: Sample characteristics compared to Census data

		Characteristics		Earnings
	Census (1990)	UI Data (1994)	Census (1990)	UI Data (1994)
Female	46.26%	48.76%	$24,939	$26,877
Male	53.74%	55.38%	$44,391	$41,328
White	68.51%	69.95%	$38,944	$38,117
Black	11.04%	12.21%	$26,444	$24,482
Other	20.45%	20.87%	$28,333	$29,295
Foreign born	17.11%	19.80%	$29,461	$29,175
US Born	82.89%	84.34%	$36,618	$35,827
Agriculture	2.62%	2.55%	$24,371	$16,717
Mining	0.29%	0.22%	$44,320	$48,440
Construction	7.35%	5.93%	$36,365	$33,817
Manufacturing	17.66%	16.96%	$36,753	$38,155
Trans. & Utilities	7.68%	6.89%	$39,878	$41,775
Wholesale trade	4.68%	7.50%	$40,741	$42,757
Retail trade	13.74%	13.59%	$26,463	$24,095
FIRE	7.51%	7.09%	$44,809	$44,884
Services	33.09%	34.85%	$34,469	$34,902
Public Admin	5.38%	4.43%	$38,793	$37,426
All	100.00%	100.00%	$35,393	$35,368

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