Inter-Industry Wage Differentials and Job Flows
Krause, M.U.

Publication date:
2002

Link to publication

Citation for published version (APA):

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

Take down policy
If you believe that this document breaches copyright, please contact us providing details, and we will remove access to the work immediately and investigate your claim.
INTER-INDUSTRY WAGE DIFFERENTIALS AND JOB FLOWS

By Michael U. Krause

January 2002

ISSN 0924-7815
Inter-industry wage differentials and job flows*

Michael U. Krause
CentER and Department of Economics, Tilburg University

December 2001

Abstract

The paper explores the relationship between job flows and wages in the U.S. manufacturing sector, where wage differentials for seemingly identical workers and job reallocation rates are shown to be negatively correlated across 3-digit industries. High wage industries have the lowest turnover of jobs, offering more secure employment opportunities. In a regression of wage differentials on industry characteristics, the role of job flows is robust to the inclusion of many variables that typically help explain the wage structure. However, average education in a worker’s industry, firm size, and capital-per-employee jointly render the coefficient on industry job flows low and insignificant.

To explain these findings, an inter-sectoral equilibrium model of the labor market with endogenous job destruction is developed. Employer-provided training in firm-specific skills provides the necessary mechanism that increases wages when job flows are low, due to the dependence of training investments on expected job duration and through exogenous differences in skill requirements. The role of average education can then be explained by a complementarity between training and observable ex-ante abilities of workers, so that average education in the regression proxies for the average amount of training that workers receive in an industry.

Keywords: endogenous job destruction, firm-specific training, industry wage structure, diffusion process, search and matching

JEL codes: J23, J31

*Thanks are due to Giuseppe Moscarini, Bill Brainard, and Truman Bewley for numerous discussions and advice. Andrew Bernard, Skander van den Heuvel, Jennifer Hunt, Robert Shiller, Wolf Wagner, and seminar participants at the EALE/Sole 2000 Conference in Milan, the OSA Institute for Labor Market Studies, Tinbergen Institute, European University Institute in Florence, Wissenschaftszentrum Berlin, and CentER, Tilburg gave helpful comments on an earlier version. Address: Tilburg University, P.O.Box 90153, 5000 LE Tilburg, The Netherlands. Email: mkrause@kub.nl
1 Introduction

The empirical findings on job reallocation (or job flows) have affected both macro- and labor economics in fundamental ways. In macroeconomics, evidence on the simultaneous creation and destruction of jobs forced researchers to acknowledge the heterogeneity of individual outcomes and to investigate its implications for the business cycle and growth. In labor economics, the findings have spurred the development of the flows approach to the labor market and brought equilibrium unemployment theory to a prominent position.

One particular set of findings concerns the variation in job flow rates across industries. For the U.S. manufacturing sector, Davis and Haltiwanger have established that both gross job creation and gross job destruction rates differ strongly across industries, each ranging between 6 and 14 percent. These rates are highly correlated: industries with low job destruction rates also have low job creation rates, which is reflected in the relatively low net growth rates of employment, on average -1.1 percent in manufacturing. Furthermore, job flows fall with the size and age of firms.

Surprisingly, there have been no explicit attempts to explore the relationship between the variation across industries in job reallocation intensities and the well-known inter-industry wage differentials. This is the topic of the paper. Using data from various sources both at the individual and aggregate levels, it documents a strong negative correlation between job flows and wages across 55 U.S. manufacturing industries, which persists even after controlling for observed worker characteristics. In other words, the central finding is that high wage industries have the lowest turnover of jobs, offering more secure employment opportunities. At first glance, this finding is puzzling since less attractive jobs should command higher wages in a competitive labor market. However, it is easily conceivable that the correlation arises because many of the factors that appear to cause industry wage differentials are inversely related to the magnitude of job flows. For example, high barriers to entry in a sector should be associated with low job reallocation rates as well as high profits-per-employee. With rent-sharing, wages will be high as well.

The paper addresses two questions. The first is whether the correlation is robust to the inclusion of industry characteristics that typically help explain the inter-industry wage structure. Regressing inter-industry wage differentials on industry characteristics shows that the partial correlation across industries between job flows and wage differentials is robust to including, individually, measures of average firm size, profits-per-employee, capital intensity, unionization, and average education of the workforce in an industry. Controlling jointly for firm size, capital intensity, and average education is sufficient to render the coefficient on job

References for the findings on job reallocation are, for example, Davis and Haltiwanger (1999), and Davis, Haltiwanger, and Schuh (1996).

Industries also differ in the cyclicity of job reallocation, with durable goods industries showing larger swings in net and gross employment changes, while non-durable industries are less cyclical.

The dataset combines the U.S. Current Population Survey, the NBER Productivity Database, and job flows statistics from the U.S. Bureau of the Census, which are based on the Longitudinal Research Database. The combined data set has 55 manufacturing industries, mostly at the 3-digit CIC level and covers the years 1975 to 1987. Details follow in Section 3.
flows both low and insignificant. The second question to be addressed is how these findings can be interpreted theoretically in a model with search and matching in the labor market and endogenous job flows.

Simulations of the calibrated labor market model show that the negative partial correlation across industries between job flows and wages cannot be generated without a mechanism that drives up the wage whenever job flows are low, thus offsetting compensating differentials for lower job security. It is shown that employer-provided training in firm-specific human capital offers such a mechanism. One possibility are of course exogenous differences in skill requirements. This explains part of the correlation. But the model highlights a second, quantitatively important mechanism based on variations in the expected duration of jobs, which is brought about by industry differences in sunk entry or job creation costs. Employers endogenously respond to the higher potential duration of employment relationships with the training they provide for newly hired workers. In the model, training translates into wages through bilateral bargaining between worker and firm.

The hypothesis that training in firm-specific skills is central to the negative correlation between job flows and wages is in fact supported by the role of capital-intensity, firm size, and average education in the regressions mentioned above. Variation in capital-intensity is likely to go along with differences in exogenous skill requirements, as more complex machinery needs a better trained workforce, while larger firms tend to have an incentive to provide training due to their ability to offer long-run employment relationships, as suggested by Idson (1996).

The effect of average education in the empirical investigation suggests a more complex interaction between job flows, training, and ability differences present in the labor market. If one assumes, following Neal (1998), that training and ability are complements in the sense that workers with better education and other ex-ante skills can be more effectively trained, then those sectors that offer more training will employ better workers. This explains why average education in an industry significantly enters in a regression that already controls for education at the individual worker’s level. Rather than reflecting the direct effect of education, it proxies for the additional reward educated workers get in sectors with more training. This is corroborated by the findings in Black and Lynch (1995), that “employers who have made large investments in physical capital relative to the number of workers or who have hired workers with higher average education are more likely to train workers within their establishments”. These authors in fact conclude that “this suggests that employer-provided training is a complement rather than a substitute to investments in physical and human capital”. In actual labor markets, these effects would be amplified if firms with more training search more intensively to improve match quality and to find the appropriate skills, which further increases wages.

The results thus emphasize the importance of firm-specific human capital in the generation of wage differentials. Furthermore, they suggest an important role of expected job

---

4As such, this finding has been documented before, for example by Dickens and Katz (1987), but not in connection with job flows.
duration, a factor typically ignored in models of equilibrium unemployment. This may be a shortcoming since these models are frequently used in the analysis of labor market institutions, which are likely to affect match and job duration.

The framework used in the theoretical analysis is a search and matching model with endogenous job flows and wage bargaining, similar to Mortensen and Pissarides (1994). There are notable innovations, however. First of all, the model allows for structural heterogeneity across industries in addition to the stochastic heterogeneity that drives gross job reallocation within industries. Equilibrium across industries obtains through worker mobility, which equalizes returns to search across sectors. Second, firms face a continuous choice as to how much firm-specific training to provide to newly hired workers. This makes explicit the effect of expected job duration on training investments. Third, sunk job creation (or entry) costs are incurred ex-ante, before a match takes place. Match-related sunk costs would directly enter wage bargaining, whereas ex-ante job creation costs merely indirectly affect wages because of the time-consuming (replacement) search if negotiations with a worker break down. It is thus possible to identify the effects of a variation in sunk job creation costs without letting them a priori enter wage bargaining. This distinguishes conceptually job creation costs from match creation costs. A final, technical, innovation of the model is that it combines equilibrium unemployment theory with the real options approach to investment decisions, with uncertainty following a diffusion process. Even though the equilibrium still needs to be simulated numerically, this allows a transparent and simple characterization the mechanisms at work, in spite of the complexity of the model.

The remainder of the paper is organized as follows. The next section provides a brief survey of related studies. Section 3 introduces the data and the econometric methodology employed and presents the empirical analysis. The model is developed and analyzed in Section 4, while Section 5 presents the results of the numerical simulations. Section 6 concludes. An appendix describes the data sources and provides further details on the model solution.

2 Related studies

The only study I know of which explicitly investigates the role of job reallocation for wages is by Belzil (2000). Using longitudinal matched worker-firm data from Denmark, he finds that plant-level net job creation increases wages for male workers at all phases of the business cycle. This is particularly the case for wages of new entrants and of low-tenure workers. He also finds that “the effects of net job creation seem independent from worker characteristics, such as education and experience.” Concerning the reallocation of workers, he finds that wages at the plant level are positively correlated with changes in worker reallocation, indicating the presence of compensating differentials. However, Belzil does not try to distinguish potential explanations of these relationships.

The focus here is different. Rather than looking at changes in wages due to net employment changes at the plant level, as Belzil does, I emphasize how average rates of gross
employment changes relate to the average wage level in an industry in the long run. These rates are best understood as a measure of the probability distribution of employment changes that plants (and hence, their workers) face, rather than the actual changes that an individual plant experiences. Thus the finding that plant-level wages rise with a plant’s net employment growth has no implication for the long-run relationship between industry wage differentials and (gross) job reallocation rates investigated here.

Two other studies more related to Belzil’s than to mine are by Dunne and Roberts (1990) and Hamermesh (1993, chapter 4). Their focus is on the effect of the risk of plant closing on plant level wages. Using data on individual manufacturing plants in the U.S., Dunne and Roberts establish that compensating differentials exist for the subset of firms that in the data appear to face the risk of shutting down. Since the authors control for industry affiliation and firm size, their results pertain to an intra-industry and intra-firm size class rather than an inter-industry correlation between wages and job security. Hamermesh rationalizes these findings theoretically.

Unfortunately, Davis, Haltiwanger, and Schuh (1996, section 3.3) do not classify plants by industry when they discuss the relationship between plant wage levels and job security. They find that “the magnitude of gross job flows falls sharply with the relative level of plant wages.[...]. Stated differently, one year survival rates are much higher for jobs at high-wage plants.” Their interpretation rests on the long-run attachment between workers and firms that higher levels of firm-specific human capital create, which drives down job flows. However, they do not consider whether the causality may run from job duration to human capital investments, as argued here, or whether the relationship also applies to the industry variation of wages.

The direct link between the duration of employment relationships and wages has been investigated by Idson (1996), but only for worker turnover and across firm-size classes. Idson gives an interpretation to his findings that is suggestive for the industry differences in job flows and wages considered here. He states that “lower [worker] turnover in large firms results from the inherently greater capacity that large employers possess to develop long-term relationships with their employees. This differential capacity stems from [...] lower failure probabilities for large firms. In addition, the higher expected duration of the employment relationships leads large firms and their employees to be more willing to invest in higher levels of on-the-job training.” Of course, once such investments are present, employers have an incentive to reduce worker turnover by hiring workers with a lower propensity to quit and by offering appropriate remuneration policies.

Finally, Abowd and Kramarz (2000) analyze longitudinal matched worker-firm data from France and Washington State. They investigate whether fixed-effects estimates of unobserved

5These gross employment changes are in fact the sum of plant-level net expansions in an industry (that is, gross job creation) and the sum of plant-level net contractions in an industry (gross job destruction).

6It should be noted that Davis et al. can only distinguish production and non-production workers. No other worker characteristics are available in their data.

7See also Davis and Haltiwanger (1999), p.2753.

8Emphasis added. A second source Idson mentions is that large employers offer more opportunities for intra-firm career development and mobility.
heterogeneity of firms and workers can account for the inter-industry wage differentials typically observed in cross-sectional data. For the U.S. sample, they find that unobserved worker fixed effects explain about half of inter-industry wage differentials and about 30 percent of the firm-size wage differential, while firm heterogeneity accounts for the remainder. Abowd, Kramarz, and Margolis (1999) find a significant effect of a plant’s survival probability on wages. Since high survival rates of jobs are inversely related to industry-level job reallocation rates, this is in line with the findings presented here.\footnote{Note that in Abowd, Kramarz, and Margolis (1999), which may be better known, the authors ascribe most industry wage differences to unobserved heterogeneity of workers. The newer results are based on exact estimation of unobserved worker and firm differences, while the 1999-paper uses an approximation procedure.}

There are several variables that stand out as correlates of the industry wage structure, which should be reported here. Dickens and Katz (1987) find that wage differentials are high in industries with high capital-to-labor ratios, high profits-per-employee, with larger establishments, and with high average education of workers.\footnote{See also Krueger and Summers (1987, 1988).} This is based on non-matched data. With longitudinal matched data, Abowd et al. (1999) report that compensation rises with the employment level of firms, capital-labor ratios and average education of the workforce. Goux and Maurin (1999) confirm that large, capital intensive, and more profitable firms tend to pay high wages. But note that while these factors are correlated with wages, they do not fully account for the inter-industry wage variation so that an unexplained residual remains, which job flows may help account for.

\section{Empirical evidence}

\subsection*{Data}

The data comes from various sources. In all regressions presented below, measures for job reallocation are those in a dataset available from the Center of Economic Studies at the U.S. Bureau of the Census.\footnote{These measures are constructed from the Longitudinal Research Database, which in turn are based on the Annual Survey of Manufactures and the Census of Manufactures.} The data is for the U.S. manufacturing sector at the 4-digit SIC level of disaggregation, covers the years 1973 to 1994, and contains job creation and job destruction rates, and employment shares of each industry. From the job creation and destruction rates one can calculate other measures of industry evolution, such as excess job reallocation, gross job reallocation, and net employment changes. The available employment shares allow easy aggregation to the 3- and 2-digit levels.

Definitions of the concepts used are as follows.\footnote{These are well known from the literature on gross job flows; see, again, Davis et al. (1996). Formal definitions are given in the appendix.} Gross \textit{job creation} is the sum of all employment increases (from expanding plants or start-ups) in an industry between period $t$ and period $t-1$ (here, yearly data is used); gross \textit{job destruction} is the sum of all employment reductions (from contracting plants or shutdowns) in an industry in the same interval; gross \textit{job reallocation} is the sum of job creation and destruction. The term gross emphasizes
that we are not looking at net changes of industry employment. Net employment growth in an industry is simply given by job creation minus job destruction. The corresponding rates are obtained by dividing by average employment in an industry between the points of measurement.

*Excess job reallocation* is a more subtle statistic. Suppose a sector exhibits no job destruction but only job creation. The rate of job creation is both the net employment gain in that sector and the job reallocation rate. This job reallocation rate is merely the turnover of jobs necessary to accommodate net employment changes. In contrast, excess job reallocation is defined as job reallocation minus the absolute value of the net employment change. It thus provides a measure of excess turbulence in a sector, ignoring net employment growth per se. Of course, if a sector exhibits no employment growth, job reallocation and excess job reallocation are the same.

The most straightforward measures for wages are contained in the NBER Productivity Database (Bartelsman and Gray, 1996). For the years 1973 to 1988, one finds total wage payments, employment, and hours worked by 4-digit SIC industry. The same is available for production workers alone. One can thus easily calculate wages per employee or per hour. The drawback is that one cannot control for individual workers’ characteristics, and thus not ascertain to what extent the results are true wage differentials rather than differences in the composition of the workforce in each industry.

To construct a wage measure that controls for observable worker characteristics, I use data from the Uniform March Files of the Current Population Survey (CPS). They cover the years 1972 to 1988 and contain a host of individual controls, for example, age, race, gender, year of education, occupation, and industry affiliation. Industry in the CPS is reported at the 3-digit level of the CIC (Bureau of the Census) classification, so that the measures from the other sources have to be aggregated from the 4-digit SIC level and converted using appropriate correspondence tables for the sectoral definitions.  

Other industry characteristics come from both the CPS and NBER. The May 1979 and May 1983 supplements to the CPS contain data on the establishment-size class a worker is employed in, his or her tenure, and whether he or she is covered by a union contract, all by 3-digit CIC industry, so that one can construct appropriate industry measures. One can also calculate average education by industry. Unfortunately, the data from the May supplements is only for two different years, and is thus less precise. From the NBER dataset, one can easily calculate an industry’s capital intensity and profits-per-employee.  

From these measures a panel of industries is constructed which covers 55 manufacturing industries over the years 1976 to 1988. While this would allow an analysis of the time series characteristics of the data, this is not the focus here. The data from the May CPS could

---

13 CIC stands for Census Industry classification. Since some SIC industry definitions have no unambiguous CIC counterpart, some sectors have to be dropped and others aggregated to a higher level where the assignment is clear. Further complications arise since the CPS data uses the 1970 CIC codes up to 1982 and the 1980 CIC codes from 1983. The detailed aggregation is given in the appendix.

14 The measure of profits-per-employee is calculated using a procedure suggested by Sanfey (1992) which is given in the appendix.
not be used then, and thus only long-run averages are compared. The main benefit of data spanning several years is that it reduces measurement error and controls for the state of the business cycle which is not possible with individual cross sections.

Econometric methodology

For any given year, the empirical model postulates an earnings equation of the form:

$$\ln W_i = X_i \beta + Z_{J(i)} \gamma + \epsilon_i$$

where worker $i$'s log wage (average hourly earnings) is related to his or her personal characteristics $X_i$ and to the industry $J(i)$ he or she is employed in. $Z_{J(i)}$ is thus a vector of dummy variables that indicate the workers’ industry, and $\beta$ and $\gamma$ are the corresponding coefficient vectors. The dummies capture the industry variation of wages not accounted for by the observed individual characteristics. The error term $\epsilon_i$ is i.i.d. across workers. The vector $X_i$ includes a typical set of controls.\(^{15}\) This equation is estimated for each of the available 13 years. The coefficients on the industry dummies are translated into estimated inter-industry wage differentials by defining $\omega_J = \bar{b}_J - \bar{b}$, the (log) variation of industry wage residuals, $\bar{b}_J$, about the mean across industries, $\bar{b}$. Note that this procedure implies that the $\beta$ vectors are allowed to vary across years, rather than being constrained to be the same.

In a second step, one regresses the estimated inter-industry wage differentials on the data on job flows and other industry characteristics, using

$$\omega_{Jt} = \alpha + \bar{Y}_J \beta_1 + (Y_{Jt} - \bar{Y}_J) \beta_2 + \nu_J + \epsilon_{Jt}$$

where $\omega_{Jt}$ is the wage differential of industry $J$ in year $t$, $Y_{Jt}$ is a vector of industry characteristics, $\nu_J$ is an industry specific fixed effect, uncorrelated with the regressors, and $\epsilon_{Jt}$ an i.i.d. error uncorrelated over time and industry. The $\bar{Y}_J$ are the year means of the $Y_{Jt}$. The $\beta_1$'s are the between-estimators of the industry effects on wages, whereas the $\beta_2$'s are the within- or fixed-effect estimators. The focus here is on $\beta_1$ only, which gives the partial correlations across industries between the year averages of wage differentials and industry characteristics. Implicitly, it is assumed that the $\epsilon_{Jt}$ average out, which is of course not exactly true because of the finite number of industries. When raw wages are used (that is, average earnings per employee, $w_{Jt}$, from the NBER Productivity database), then $\omega_{Jt} = \ln w_{Jt}$.\(^{16}\)

---

\(^{15}\)These variables are: a measure of potential experience, education and its square, 6 age dummies, 8 occupational dummies, 11 region dummies, a sex dummy, 2 race dummies, 4 marital status dummies, ever married $\times$ sex interaction, education $\times$ sex interaction, education squared $\times$ sex interaction, 6 age $\times$ sex interactions, and a constant. The sample is restricted to full-time employees who are older than 16 years. Following Katz and Murphy (1992), potential experience is approximated by $\min(\text{age} - \text{years of schooling} - 7, \text{age} - 17)$.

\(^{16}\)The use of cross-sectional data in the presence of heterogeneity and the use of aggregates in micro wage regression has the pitfall of creating a number of biases. This results from the omission of unobserved worker and firm fixed effects which could be estimated using matched longitudinal data on both workers and their respective employers. Without employer information even the estimated fixed effects of workers are biased (as they include an employment duration weighted average of the firm fixed effects that a worker enjoyed over
Results

Figure 1 shows the relationship between excess job reallocation rates and estimated inter-industry wage differentials in manufacturing, averaged over 13 years for each industry. The simple correlation is -.66. (The numbers are the approximate CIC 1980 codes.) Examples for high-wage, low reallocation sectors are pulp, paper, and paperboard mills (160), petroleum refining (200), and photographic equipment and supplies (380). Low-wage, high reallocation sectors are leather products (220), miscellaneous wood products (241), and apparel and accessories (151). The appendix gives the complete classification.¹⁷

![Figure 1: Inter-industry wage differentials and excess job reallocation, average by sector across 1976-1988](image)

To pick one specific case for a high wage industry with low job flows, take plastics (180). Wages controlled for individual characteristics are 10.7 percent higher than average in the manufacturing sector and average excess job reallocation is 6.5 percent. Recall the definition of excess job reallocation which implies here that each period only about 3.25 percent of jobs in that sector vanish, with an equal number newly created, in excess of what is needed to accommodate net employment growth. Production in that sector is typically capital

his or her career). The use in a wage regression of aggregates such as the average capital-to-labor ratio in an industry rather than actual capital intensity of an individual firm obviously leads to a loss of information. Abowd, Kramarz, and Margolis (1999) and Abowd and Kramarz (2000) provide a formal illustration of these biases. See also Moulton (1986). As mentioned in section 2, about half of inter-industry wage differentials is likely to arise from person effects, while the rest arises from firm effects.

¹⁷Note that logging (230) has been excluded from the analysis. The nature of that industry suggests that most of its measured job reallocation is spurious.
intensive, about half of firms have more than 500 employees, and profitability is high. At the other end of the spectrum is apparel (151). Wages are 18.4 percent below the manufacturing average, and excess job reallocation is 19.5 percent on average. This industry is particularly labor intensive, only 10 percent of firms have more than 500 employees, and profitability is relatively low.

Table 1: Regression of wages on job reallocation measures (between group estimator)

| Regression of average wages (1-4) and wage differentials (5-8) on job flow measures |
|---------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|
|                                | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| job creation                   | .0002 |    |    |    | -.022 |    |    |    |
|                                | (0.01) |    |    |    | (3.22) |    |    |    |
| job destruction                | -.055 |    |    |    | -.006 |    |    |    |
|                                | (3.10) |    |    |    | (1.01) |    |    |    |
| job reallocation               | -.028 |    |    |    | -.014 |    |    |    |
|                                | (4.64) |    |    |    | (5.68) |    |    |    |
| excess job reallocation        | -.035 | -.035 |    |    | -.017 | -.017 |    |    |
|                                | (5.20) | (5.49) |    |    | (6.55) | (6.47) |    |    |
| net employment growth          | .028 | .042 |    |    | -.008 | -.0008 |    |    |
|                                | (1.56) | (2.54) |    |    | (1.32) | (0.14) |    |    |
| $R^2$ – between                | .34 | .34 | .34 | .41 | .38 | .38 | .45 | .45 |
| # of sectors                   | 55 | 55 | 55 | 55 | 55 | 55 | 55 | 55 |
| # of years                     | 16 | 16 | 16 | 16 | 13 | 13 | 13 | 13 |

Absolute values of the t-statistics are in parentheses.

Table 1 reports the results from regressing wages on measures of job flows. There are two measures of wages: average (raw) wages in an industry without controlling for worker characteristics (total wage bill divided by employment, columns 1 to 4) and inter-industry wage differentials (columns 5 to 8). The coefficients reported are the between-group estimates. First consider job creation and job destruction rates only. One finds in column (1) that job creation is unrelated to average wages, whereas job destruction and wages are significantly negatively correlated. In contrast, controlling for observed worker and job characteristics in column (5) leaves job destruction insignificant but reveals an inverse wage-job creation relationship. The difference in the coefficients on job creation may indicate a composition effect in that sectors with relatively high job creation rates employ observedly better worker and offer better jobs. This effect vanishes in column (5). The negative coefficient on job creation shows that high job creation sectors (conditional on job destruction) offer lower rents or employ less able (but unobservedly so) workers. These lower rents may be due to the fact that the fraction of newly created jobs is high, tenures are lower, so that workers did not acquire match-specific capital. The fall in the coefficient on job destruction suggests that high job destruction sectors (conditional on job creation) tend to employ observedly
less able workers on worse jobs.

Both job reallocation and excess job reallocation are significantly negatively related to wages. The coefficients on the job flow measures are about 50 percent lower for inter-industry wage differentials. This indicates that about half of the between-industry correlation between job flows and raw wages is due to observed worker and job characteristics that the wage regression controls for. It also shows that the correlation applies to raw wages and wage differentials alike. Taking account of net employment growth has no effect on the relationship between wages and job flows, as can be seen in columns 3 and 4.\textsuperscript{18} Interestingly, the positive coefficient on employment growth becomes insignificant while job flows become even more significant when wage differentials are used instead of raw wages. In line with the finding for job creation and destruction, sectors that grow faster appear to have workers with better observable characteristics and to have better job characteristics.

Table 2: Regression of wage differentials on industry characteristics

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>excess job reallocation</td>
<td>-.013</td>
<td>-.011</td>
<td>-.015</td>
<td>-.012</td>
<td>-.0047</td>
<td>-.0045</td>
<td>-.0037</td>
<td>-.0031</td>
</tr>
<tr>
<td></td>
<td>(5.27 )</td>
<td>(4.29 )</td>
<td>(5.57 )</td>
<td>(5.32 )</td>
<td>(2.02 )</td>
<td>(1.96 )</td>
<td>(1.66 )</td>
<td>(1.50 )</td>
</tr>
<tr>
<td>capital intensity</td>
<td>.07</td>
<td>.39</td>
<td>.31</td>
<td>.46</td>
<td>.36</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.39 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>profits-per-employee</td>
<td>1.27</td>
<td>.82</td>
<td>1.05</td>
<td>.31</td>
<td>.53</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.65 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>firm size</td>
<td>.22</td>
<td>.26</td>
<td>.23</td>
<td>.22</td>
<td>.18</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.77 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>unionization</td>
<td>.146</td>
<td>.093</td>
<td>.132</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.12 )</td>
<td>(1.83 )</td>
<td>(2.84 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>average education</td>
<td>.051</td>
<td>.028</td>
<td>.034</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.92 )</td>
<td>(2.99 )</td>
<td>(3.75 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Absolute values of the t-statistics are in parentheses*

The regressions in Table 2 include various factors that are likely to help account for the correlation between job flows and wages. Focus here is on excess job reallocation only. This is because job creation and job destruction rates show no coherent pattern across regressions and are often insignificant, net employment growth is insignificant in almost all specifications and does not affect the coefficient on excess job reallocation, and, finally, job reallocation rates are not considered because excess job reallocation has a clearer interpretation. At this point be reminded that the regressions are not meant to reflect any causality. They report

\textsuperscript{18} The same is true for job reallocation, not reported here.
partial correlation coefficients between the left-hand side variable and a set of other variables, and merely help assess the robustness of the partial correlation between wage differentials and job flow rates.

In the first three columns, four variables are considered: capital intensity, profits-per-employee, firm size, and unionization. The positive relationship of each variable with wages is in line with the previous findings reported earlier. Capital intensity is likely to be negatively correlated with job flows because of its relationship with entry and other sunk job creation costs. Similarly, entry barriers that drive down job flows generate market power for incumbent firms and thus generate high profits per employee. For firm size, it is well known that large firms exhibit lower job flows, even holding age constant.\textsuperscript{19} Union coverage has been included to reflect the possibility that sectors with more stable employment opportunities and potentially higher attachment between workers and firms have unionized workforces.

The most surprising result is that the importance of excess job reallocation is barely affected when any of the above mentioned variables is included separately.\textsuperscript{20} The largest reduction in the coefficient, of about a third, is caused by firm size. But also here, excess reallocation remains highly significant. None of the potential explanations works if controlled for in isolation. However, taking firm size, capital intensity, and profits-per-employee in conjunction, the partial correlation between job flows and wage differentials is sharply reduced. The coefficient on job flows falls by more than half and comes close to insignificance (at the 5 percent level). The only variable so far not considered is average education of the workforce in an industry. As mentioned earlier, many studies of the wage structure find a significant effect even though individual workers’ wages have been controlled for the respective worker’s education. It leads to a fall in the coefficient on job flows and has a significant effect on wages. When included along with the other variables, the coefficient on job flows falls to its lowest level and becomes insignificant.\textsuperscript{21} It should be noted that capital intensity and firm size alone also reduce the coefficient on job flows (to -.004 with a p-value of 0.106). However, when profits are included, job flows are significant. This indicates some strong collinearities between profits-per-employee and the other variables.

Similar results obtain when (gross) job reallocation is considered instead of excess job reallocation. Here, firm size, capital intensity, and average education are sufficient to reduce the coefficient on job reallocation to statistical and economic insignificance (0.002 with a p-value of 0.302). Average education plays a central role in that no other combination of variables delivers this effect. Profits-per-employee have no marginal contribution. Apparently, average education captures most of the contribution of profits, which may arise if firms

\textsuperscript{19}See Davis and Haltiwanger (1999).

\textsuperscript{20}Capital intensity and profits-per-employee are included together mainly to save space.

\textsuperscript{21}Of course, each of the other regressors in column (8), when included last, leaves excess job reallocation insignificant. Average education is added last here because it is not among the set of variables that theory suggests should be related to the wage structure. It is also the least likely to be related to job flows, which is a surprising finding. (The correlation between average education and job flows is -.34.) Furthermore, in most specifications, other combinations of three industry characteristics are not sufficient to render job flows low and insignificant.
can exploit complementarities between skills that translate into higher profits (and wages).

The empirical analysis suggests that the partial correlation across industries between job flows and wage differentials is robust to the inclusion of other industry characteristics that typically help explain the wage structure. The goal of the next section is to develop a model with endogenous job flows that is consistent with these findings. An important aspect of such a model is that it must allow for a mechanism that drives up wages whenever job reallocation is low, without presupposing such a relationship. Further, this mechanism must be consistent with the findings mentioned last, in particular that average education in an industry seems to play an important role.

4 The model

Firms

An industry contains a continuum of firms, whose output is sold in a competitive, industry-wide market. Each firm consists of one job. Output depends on a worker’s job-specific human capital, but the profitability of the job is uncertain in terms of a randomly evolving, idiosyncratic flow cost, $x_t$. The instantaneous profit flow of a producing firm is given by

$$\pi_{J,t} = Pf(h) - x_t - w_t - k.$$ 

where $P$ is the competitive price of the firm’s output, determined by free entry and taken as given by firms. The output of a worker as a function of firm-specific human capital, $f(h)$, has the properties $\frac{\partial f}{\partial h} > 0$ and $\frac{\partial^2 f}{\partial h^2} < 0$. The wage is $w_t$, determined by Nash bargaining, and $k$ is a constant maintenance cost, given by $k = \delta K$, with depreciation rate $\delta$ and $K$ the capital stock that is necessary for production. Endowing a newly hired worker with $h$ requires a lump-sum training cost specified below. Training is employer-provided and human capital $h$ is constant over the remaining lifetime of the employment relationship. The job-specific flow cost evolves stochastically according to the geometric Brownian motion

$$dx_t = \mu x_t dt + \sigma x_t dz_t,$$

with drift $\mu$, variance $\sigma^2$, and $z_t$ a Wiener process. The realizations of $z_t$ are idiosyncratic to the firm while the parameters $\mu$ and $\sigma$ are the same for all firms in a given industry.\(^{23}\)

A firm enters the industry at an exogenously given level of flow costs, $x_C$, normalized to unity. Upon entry, the firm pays a lump-sum job creation or entry cost $C$, after which it searches for a worker. The job creation cost is the sum of a pure sunk cost, $S$, and the cost for the capital stock, $K$, part of which may be sunk, too. Search is subject to the standard

\(^{22}\)Industry subscripts are ignored as long as no confusion arises.

\(^{23}\)Even though uncertainty is represented by the random evolution of variable costs, it may be useful to think of $x_t$ more generally as reflecting uncertainty in a firm’s market demand, its productivity, and input prices. Pissarides (2000) calls $x_t$ the variable costs of the firm. Another plausible formulation would have been to let revenue be random. However, this leads to the complication that the size of a firm cannot be restricted to one.
matching frictions, represented by a matching function. After a firm provides training in firm-specific skills, production starts. The wage is determined through Nash bargaining over the surplus that accrues after training. If the job becomes unprofitable, the worker is fired and the job must be destroyed, yielding a scrap value $D = \kappa K$, with $0 \leq \kappa \leq 1$.

The Bellman equation for the expected present value $J$ of a filled, producing, job is given by

$$rJ(x_t, h) = Pf(h) - x_t - w_t - k + E[dJ(x_t, h)] / dt$$

with $r$ the economy-wide, annual interest rate and $E$ the expectation operator. The equation has the usual interpretation of relating the return to the asset “job” to a flow dividend per unit time plus an expected capital gain. The value of a newly created, vacant job at the job creation threshold $x_C$ is similarly given by

$$rV(x_C) = -k + q(\theta)[J(x_C, h) - V(x_C) - T(h)],$$

where $q(\theta)$ is the industry-specific flow (Poisson) probability of finding a worker as a function of labor market tightness $\theta = v/u$ ($v$ and $u$ are the measures of vacancies and unemployment respectively). $T(h)$ is a convex lump-sum training cost. With free entry, the price $P$ and labor market tightness $\theta$ will adjust such that $V(x_C) - C = 0$. The problem of the firm is to find both a job destruction threshold $x_D$ and an optimal level of training that maximizes the value of a new job, that is,

$$\max_{x_D, h} J(x_C, h) - T(h).$$

The number of matches formed in an industry is a function of the number of vacancies posted by firms and the number of searching (unemployed) workers in that industry. There is no search on the job. Let the sectoral matching function at any point in time be

$$M = U^m V^{1-m}$$

with $0 < m < 1$. Industry subscripts are still ignored. The rate at which vacancies are filled is $M/V = (U/V)^m = q(\theta)$ where $\theta = V/U$. Thus, $\partial q(\theta) / \partial \theta < 0$. Equivalently, one can express $\theta$ in terms of the vacancy rate $v = V/L$ and the unemployment rate $u = U/L$, with $L$ representing the number of workers in a sector (both unemployed and employed). Similarly, the rate at which workers find jobs is $M/U = (U/V)^{m-1} = \theta q(\theta)$, with $\partial \theta q(\theta) / \partial \theta > 0$.

**Workers**

Risk-neutral workers in the homogeneous workforce search for jobs across industries. Using the same interest rate as firms, the value of being unemployed to a worker who searches for a job in some industry $i$ is given by the arbitrage equation:

$$rU_i = b + \theta_i q(\theta_i) (W^e_i - U_i)$$

(1)

$^{24}$The role of this assumption is discussed at the end of section 5.
where the flow value of the asset “unemployment” is equated to a flow benefit \( b \) (the flow value of leisure or an unemployment benefit) and an expected capital gain. The latter depends on the flow probability \( \theta_i q(\theta_i) \) of finding a job times the change in value as a result of being hired. \( W^e_i \) is the expected value of employment upon being hired in industry \( i \). Workers are mobile and join the sectoral unemployment pool that offers the highest expected return, which implies that \( U = U_i \) for all \( i \). However, \( W^e_i \) and \( \theta_i q(\theta_i) \) will depend on each industry’s structural parameters. The value \( W_{it} \) when employed in industry \( i \) is given by:

\[
rW_{it} = w_{it} + E [dW_{it}] / dt
\]

which depends on the wage yet to be determined and the expected change in the value of employment.

**Wage bargaining**

Costly search and training generate a surplus over which worker and firm bargain. Here, it is assumed that the surplus after training is split in a Nash bargain. However, the firm posts the wage before training takes place, and it remains constant at \( w_c \) over the lifetime of the job, there is no renegotiation.\(^{25}\) In effect, the firm correctly anticipates the wage that would arise in negotiations after training. There is no two-tier wage contract in which the firm can extract the cost of training from the worker. More discussion follows below. Nash bargaining implies

\[
W(x_C) - U = \frac{\lambda}{1 - \lambda} (J(x_C) - V(x_C))
\]

with the relative bargaining powers \( \lambda \in [0, 1] \) for the worker and \( 1 - \lambda \) for the firm. \( U \) and \( V(x_C) \) are their respective fallback options should the match break up. With the assumed constant wage, \( w_t = w_c \), the worker’s Bellman equation becomes

\[
rW(x_t) = w_c + E [dW_t] / dt.
\]

**Equilibrium**

**The job destruction threshold**

As in any model with endogenous job destruction, the job destruction threshold, or reservation cost, \( x_D \), is essential for the determination of wages and job flows. It is found with the help of two optimality conditions that must hold at \( x_D \), namely a value matching condition, \( J(x_D, h) - D = 0 \), and a smooth pasting condition \( \partial J(x_D, h) / \partial x_D = 0 \). These conditions and a boundary condition for \( x_t \to 0 \) determine the solution to the second-order differential

\(^{25}\)One can show that in this setup, the wage would endogenously remain constant over a large range of outcomes even if it is not constrained to be constant. This is due to the fact that entry occurs at a level of cost that is not the lowest possible, so that profits can stochastically increase, rather than only decrease, as in most other models.
equation that arises when one uses Ito’s Lemma to substitute $E[dJ(x_t, h)]/dt$ in the equation for $J(x_t, h)$ above. The details are given in the Appendix. Solving the value matching condition for $x_D$, one gets:

$$x_D = \frac{\beta}{\beta - 1}(r - \mu) \left[ \frac{Pf(h) - w_c - k}{r} \right] - D$$  \hfill (2)

where $\beta > 1$ is the positive root of the fundamental quadratic associated with the differential equation for $J(x_t, h)$. This condition is analogous to the critical investment schedule as found in, for example, Dixit and Pindyck (1994, p.145), where the wedge between the critical value for investment over the sunk cost of investment is $\beta(r - \mu)/(\beta - 1)$. Here, of course, the wedge is over the net cost of disinvestment, which is the annualized flow return from production minus the scrap value. The higher this cost, the higher $x_D$ and thus the flow cost $x_t$ the firm is willing to bear before it stops producing.

Since $P$, $h$, and $w_c$ are endogenous, this equation is not sufficient to determine $x_D$. Conveniently, one can use the free entry condition to eliminate $Pf(h) - w_c - k$. To see this, remember that, from free entry, $V(x_C) = C$, so that $rC = -k + q(\theta)[J(x_C, h) - C - T(h)]$ after substituting into the asset value of a vacant job. Rearranging gives $J(x_C, h) = C + [rC + k]/q(\theta) + T(h)$. This can be set equal to the solution of $J(x_t, h)$ at $x_C = 1$ to yield\(^{26}\)

$$\frac{Pf(h) - w_c - k}{r} - \frac{1}{r - \mu} \left[ 1 - \frac{1}{\beta}x_D^{1-\beta} \right] = C + \frac{rC + k}{q(\theta)} + T(h).$$

Rearranging and inserting into (2) results in an implicit definition of $x_D$ as a function of structural parameters and the two endogenous variables $\theta$ and $h$:

$$x_D^{1-\beta} + (\beta - 1)x_D = \beta + \beta(r - \mu) C + \frac{rC + k}{q(\theta)} + T(h) - D.$$  \hfill (3)

Note that an increase in the right hand side leads to an increase in $x_D$. Obviously, it is increased by higher entry costs $C$, a lower scrap value $D$, and higher training costs $T$. Furthermore, it is increased by a higher expected forgone output during search for a worker. Equation (3) is analogous to what Pissarides (2000) and Mortensen and Pissarides (1999) call the job creation condition.

**Job reallocation**

Due to the diffusion properties assumed for flow costs, one can find explicit expressions for the rate of job destruction, using the associated Fokker-Planck equation. The rate of job destruction is given by

$$\text{Flow}(x_D) = -\frac{1}{2}\sigma^2 x_D^2 \Phi'(x_D) = \frac{\mu}{2} - \frac{1}{\ln x_D}.$$  \hfill (4)

\(^{26}\) $J(x_C, h)$ is given by

$$J(x_C, h) = \frac{Pf(h) - w_c - k}{r} - \frac{1}{(r - \mu)}x_C + \frac{1}{(r - \mu)} \frac{1}{\beta}x_C^{1-\beta}.$$
where $\Phi'(x_D)$ is the left derivative of the distribution of jobs at $x_D$. One can see from the middle term that the mass of jobs that hit $x_D$ depends on the shape of that distribution. The steeper the distribution, the higher the job flow: a larger mass of firms is close to the threshold, and therefore more likely to hit it, given the drift and variance of the process.

**Wages**

Since the prospects for an employed worker are governed by the geometric Brownian motion for $x_t$ defined above, Ito’s Lemma applies here as well, and can be used to determine $E[dW_t]/dt$ in the wage equation. Again, this results in a second-order differential equation, which can be solved using the appropriate boundary conditions. The boundary condition at the point where a match breaks up, $rW(x_D) = rU$, implies that one can rewrite the solved Bellman equation as $rW(x_t) = w_c + (rU - w_c)x_D^{-\beta}x_t^\beta$. Bargaining takes place at $x_t = x_C = 1$, so the wage is

$$w_c = \frac{1}{1 - x_D^{-\beta}} \frac{3}{4} W(x_C) - Ux_D^{-\beta}.$$

It remains to determine $W(x_C)$. Using the fact that $J(x_C, h) - V(x_C) = J(x_C, h) - C = [rC + k]/q(\theta) + T(h)$ from the discussion above, the bargaining equation implies

$$W(x_C) = U + \frac{\lambda}{1 - \lambda} \frac{\hat{A}}{rC + k} + T(h),$$

so that substituting into the wage yields

$$w_c = rU + \frac{r}{1 - x_D^{-\beta}} \frac{\lambda}{1 - \lambda} \frac{\hat{A}}{rC + k} + T(h).$$

This equation shows the main intuition of the model. Ceteris paribus, a higher $x_D$ implies a lower wage. This is because of compensating differentials for a higher expected duration of the job. On the other hand, higher job creation costs $C$, higher flow cost of capital $k$, or a higher expected vacancy duration $1/q(\theta)$ lead to a higher wage. This reflects the forgone revenue the firm suffers if the match broke up, increasing the bargaining position of the worker. Of course, higher job creation costs also affect the destruction threshold, and the resulting increase in the duration of the job depresses the wage. It also creates an incentive for the firm to invest in training $h$.

There are a few important differences to the setup in other search and matching models, such as Mortensen and Pissarides (1994). First, the job creation cost is paid before the match forms. One should think of firms incurring most of the sunk creation cost (administration, research and development, planning and construction of a plant) in advance. Thus, the full value of $C$ does not appear in the wage equation, which would be the case if creation cost were paid ex-post. However, $rC$ appears because it reflects the forgone revenue if the firm needed to replace the worker. Secondly, the model imposes a one-tier wage structure. That is, workers do not pay for the subsequently earned rents by accepting a low starting wage. Instead, a uniform “insider” wage is paid, for the same reasons provided by Mortensen and
Pissarides (1999): Once hired, workers have an incentive to renege on the lower initial wage, so a hold-up problem arises. Third, there is a direct effect of the perceived security of the job on the wage, reflected by $x_D$.

**Training**

The choice of training has two effects on the profits of the firm. Profitability and training costs are directly affected. But the increase in productivity also affects the job destruction threshold by making the firm more reluctant to destroy the more valuable job that carries a more valuable match. The firm chooses training to maximize (using the fact that $x_C = 1$):

$$J(x_C, h) - T(h) = \frac{Pf(h) - w_c - k}{r} - \frac{1}{r - \mu} \left( 1 - \frac{1}{\beta} x_D^{1-\beta} \right) - C - \frac{rC + k}{q(\theta)} - T(h)$$

where the product price, wage, and labor market tightness are taken as given. The first order condition is

$$\frac{Pf'(h)}{r} + \frac{\beta - 1}{(r - \mu)^2} \frac{x_D^{-\beta}}{\partial h} - T'(h) = 0 \quad \text{with} \quad \frac{\partial x_D}{\partial h} = \frac{\beta(r - \mu)}{\beta - 1} \frac{Pf'(h)}{r}$$

where the latter follows from the job destruction condition (2). Note that there is no effect of $x_D$ on the wage because the wage is already negotiated when the firm provides training. This level of training, however, is correctly anticipated when the wage is set. However, training does affect the job destruction threshold. Inserting yields

$$\frac{Pf'(h)}{r} \left( 1 - x_D^{-\beta} \right) = T'(h)$$

This condition shows directly the role of $x_D$ for the training choice: the higher expected duration of the job that comes with a higher $x_D$ increases the marginal return to training.

**One-sector general equilibrium**

Before analysing the inter-industry structure of wages, one needs to determine the overall value of unemployment in the average industry. For the time being, ignore the endogeneity of training costs, and write $T$ instead of $T(h)$ and $f$ instead of $f(h)$. Using the bargaining equation, the Bellman equation for unemployed workers can be rewritten:

$$rU = b + \theta q(\theta)(W^e - U) = b + \theta q(\theta) \frac{\lambda}{1 - \lambda} ((rC + k)/q(\theta) + T).$$

Inserting into the wage equation gives the equilibrium wage

$$w_c = b + \frac{\lambda}{1 - \lambda} \theta q(\theta) + \frac{r}{1 - x_D^{-\beta}} \frac{rC + k}{q(\theta)} + T.$$

A second equation for the wage comes from the job destruction condition (2). Solving it for the wage and setting equal to the equilibrium wage gives an implicit relationship between $x_D$ and $\theta$

$$Pf - k - \frac{r - \mu}{r - \mu} \frac{\beta - 1}{\beta} x_D - rD - b - \frac{\lambda}{1 - \lambda} \theta q(\theta) + \frac{r}{1 - x_D^{-\beta}} \frac{rC + k}{q(\theta)} + T = 0. \quad (6)$$

This gives a mildly downward-sloping curve in $(x_D, \theta)$-space, whereas the job creation condition (3) implies an upward-sloping curve.
5 Calibration and simulation

This section discusses the parameter values and the benchmark general equilibrium around which the industry simulations take place. Some of the numerical values that are used as benchmarks for each parameter will remain constant in all simulations; others will be varied to reflect certain dimensions of industry heterogeneity. The time period is one year. The common interest rate for firms and workers is $r = 0.05$. Capital depreciates at a rate $\kappa = 0.1$. Following convention, the bargaining share of workers is set to $\lambda = 0.5$ and the unemployment benefit is set to $b = 0$.

The levels of certain parameters are only defined relative to other variables. The initial values for capital, wages, and job destruction in the benchmark industry were chosen as follows. The starting value for capital-per-worker is normalized to $K = 0.6$, which may be interpreted as 60,000 (1987) dollars per worker, roughly the average for the manufacturing sector. By the one job-one worker assumption, $K$ is equivalent to the capital intensity. The scrap value is set to $D = 0.9K$. Revenue is normalized to $Pf(h) = 4$. Productivity of a worker is given by $f(h) = g + h^{1-d}/(1-d)$ with $d = 0.4$, $g = 10$. The latter reflects general human capital of workers. Training costs are given by $T(h) = th$.

The stochastic process for the flow cost $x_t$ is assumed to have drift $\mu = 0.04$ and standard deviation $\sigma = 0.05$. This implies a drift for the logarithm of $x_t$ (or the percentage change) of $\nu = \mu - 1/2\sigma^2$. For a stationary distribution to obtain in steady state, $\nu$ must be positive, and in this case is $\nu = 0.025$, reflecting the fact that existing firms’ conditions tend to worsen in the long run. A reason for this can be that the technology of new firms increases while existing firms fall behind. One could model this explicitly by letting the entry of new, productive firms drive down the price, so that profits fall. Instead, the shortcut was taken to let costs move up.\footnote{For an example of an explicit solution, see Krieger (1998). He normalizes his equation system by a dynamic scale factor, so that a stationary optimization problem obtains.}

The table summarizes the assumptions along with the range of values for wages and job flows that the simulations aim to replicate.

The general equilibrium of this economy can be found numerically using equations (3) and (6). Training is taken as given for the average industry and the training cost is normalized to equal 10 percent of yearly revenue. The solution is a pair of labor market tightness and the job destruction threshold as functions of the underlying parameters. From this, one can calculate the wage and the job destruction rate. For the benchmark calibration, the equilibrium values are $\theta^* = 4.5$ and $x_D^* = 1.46$, which corresponds to a job destruction rate of 9.3 percent. The equilibrium wage is $w^* = 2.8$.

Inter-industry wage differentials and job flows

Simulating the industry structure of job flows and wages requires a change in perspective. Variables that are endogenous in general equilibrium are parameters for the industry equilibrium. Differences in the structural parameters of an industry, such as job creation costs, leave the value of searching (being unemployed) in that sector unaffected, even if there are
Table 3: Parameter calibration and starting values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Idiosyncratic uncertainty</td>
<td>( \sigma = 0.1, \mu = 0.04, \nu = 0.025 )</td>
</tr>
<tr>
<td>Interest rate</td>
<td>( r = 0.05 )</td>
</tr>
<tr>
<td>Productivity</td>
<td>( f(h) = g + h^{1-d}/(1 - d) )</td>
</tr>
<tr>
<td>General human capital</td>
<td>( g = 10 )</td>
</tr>
<tr>
<td>Training cost</td>
<td>( T(h) = th )</td>
</tr>
<tr>
<td>Depreciation rate</td>
<td>( \kappa = 0.1 )</td>
</tr>
<tr>
<td>Bargaining share</td>
<td>( \lambda = 0.5 )</td>
</tr>
<tr>
<td>Benchmark capital per job</td>
<td>( K = C = .6 )</td>
</tr>
<tr>
<td>Range for job creation cost per job</td>
<td>( C \in [0.6, 2.2] )</td>
</tr>
<tr>
<td>Scrap value</td>
<td>( D = 0.9K )</td>
</tr>
<tr>
<td>Average job destruction rate</td>
<td>( JD = 9.7 )</td>
</tr>
<tr>
<td>Target range for job destruction</td>
<td>( JD \in [6.5, 13.3] )</td>
</tr>
<tr>
<td>Target range for wages</td>
<td>( w \in [0.8w^<em>, 1.2w^</em>] )</td>
</tr>
<tr>
<td>Revenue</td>
<td>( Pf(h) = 4 )</td>
</tr>
<tr>
<td>Matching function</td>
<td>( m = 0.5 )</td>
</tr>
</tbody>
</table>

effects on the value of being employed. Again, this is due to the mobility of workers that equalizes returns to search across sectors. What does adjust, however, is the mass of workers relative to the mass of vacancies in a sector, and that in turn affects labor market tightness. Given labor market tightness and the other structural parameters, one can calculate the resulting industry job flows and wages. This section proceeds by first analysing the case without endogenous training to illustrate the workings of the model more clearly, and to show the difficulty to explain high wages in low job flow industries when training investments are absent. Then, endogenous training investments are included.

No training

The core equations determining the equilibrium in an industry are (1) and (4), replicated here for convenience, using industry subscripts:

\[
\begin{align*}
    r_U &= b + \theta_i q(\theta_i) (W_i^e - U) \\
    W_i(x_C) - U &= \frac{\lambda}{1 - \lambda} \left( \frac{\tilde{A}}{q(\theta_i)} + T \right) \\
    W_i^e &= W_i(x_C) \quad \text{and} \quad T(h_i) = T \quad \text{in all industries}. 
\end{align*}
\]

where \( W_i^e = W_i(x_C) \) and \( T(h_i) = T \) in all industries. Given the uniform level of training, these equations uniquely determine the value of finding employment in an industry, \( W_i^e \), and the corresponding labor market tightness, \( \theta_i \). Given \( \theta_i \), one can obtain \( x_{D,i} \) using equation (3) and finally \( w_{c,i} \) by (5). Note that when deep parameters change, the value of a job is affected, which in turn encourages entry or exit and thus a corresponding price change. The condition that determines \( x_{D,i} \) already incorporates this fact.
In the simulation, the sunk cost of job creation is varied by as much as is necessary to generate the range of job reallocation rates observed in the U.S. manufacturing sector, which in this case is from $C = 0.6$ to $C = 2.2$. Capital $K$ is held constant which reflects that capital has been controlled for in the regression of wage differentials on job flows. The result is shown in Figure 2.

The graph shows a positive correlation between job flows and wages. Note that because of the steady state of the model, job reallocation and excess job reallocation are the same in the model. The wage is depicted in a range of 5 percent below and above the average wage, which indicates that the predicted variation of the wage is very low compared to the empirical range. However, the central result is that the correlation is positive, in contrast to the data. The variation in wages and job flows is due only to the variation in sunk job creation cost.

The intuition for this lies in the compensating differentials that firms have to offer in the presence of higher unemployment risk. High job creation costs in an industry increase the expected duration of a job which induces workers to accept a lower wage. Several simultaneous effects take place. Higher job creation costs affect the wage directly through a stronger bargaining position of the worker, reflected by the term $rC$ in the wage equation. Against this works an increase in labor market tightness for workers because less jobs are created, which strengthens firms’ bargaining position. The overall effect on $(rC + k)/q(\theta)$ is positive. Nevertheless, the fall in job reallocation and thus rise in job duration, due to the
increase in $x_D$, leads to a decline in $1/(1-x_D^β)$, reflecting workers’ willingness to accept lower wages. Since the wage falls with falling job flows, the latter effect outweighs the increase in $(rC + k)/q(θ)$ in the wage equation (5).

Two types of general equilibrium effects are at work. One is the adjustment of prices. Rising job creation costs reduce entry into an industry and thus drive up the industry price. This in turn makes firms more reluctant to destroy jobs, as can be seen in (2). The other effect is on labor market tightness. A reduced creation of jobs reduces the likelihood of workers finding a job in an industry, thus weakening their bargaining position.

**Training**

The inclusion of training investments requires a parametrization of the training function and the cost of training. The parameters chosen here are $d = 0.4$ and $g = 10$. The factor $t$ in the training cost function is actually not chosen ex-ante, but the result of the calibration of the general equilibrium version of the model, which required total training cost to equal 10 percent of yearly revenue. Thus, $t$ turned out to equal 5.9. For the industry equilibrium, this and the value of unemployment are treated as parameters. Varying job creation costs in the same range as above results in Figure 3.

![Job Reallocation and Wages with Training](image)

When allowing firms to invest in their workers’ firm-specific skills, the predicted correlation between job flows and wages is negative as found in the data. Higher training in
industries with higher job creation costs offsets the negative effect that higher job security has on the wage. Technically, the increase in $T(h)$ outweighs the fall of $1/(1 - x_P^\beta)$ in the wage equation. Through bargaining, a worker can extract part of the replacement costs that the firm would incur if the match broke up. Workers in such industries not only enjoy the benefits of higher job security, but also obtain higher rents from training. In this figure, the range for wages depicted is that found for wage differentials in the data (20 percent above and below the average). The model’s predicted range for wages (about 5 percent below and above the average) roughly corresponds to the empirical range found after controlling for industry characteristics. Another interaction that takes place is an increase in training that further raises the job destruction threshold, which affects job duration and in turn feeds back into training. Additionally, since higher job creation costs reduce entry, the higher industry price increases the marginal return to training.

Another important possibility is that industries differ by skill requirements. This is obvious for capital-intensive industries, where workers may have to learn how to operate sophisticated machinery. An independent variation of skill requirements can be modelled by varying the parameter of the training function, $d$. A higher return from training increases training and therefore workers’ wages. For firms, higher training costs increase the job destruction threshold and thus reduce the job destruction rate. Furthermore, higher wages attract more workers into such a sector, so that labor market tightness (for firms) falls. The range of wages generated by industry differences in skill requirements is not reported here but is similar in magnitude and sign to that arising from differences in sunk job creation costs.

Variation in the bargaining power of the worker leads to a positive correlation between wages and job destruction. A higher wage results if the worker obtains a larger share of the joint surplus of the match with the firm. Furthermore, a lower expected duration of the job must be compensated with a higher wage. For the firm, the fact that a larger fraction of the surplus goes to the worker reduces the incentive to train so that training falls. Job destruction rises both from the fall in training and from the fall in labor market tightness that results from the increased attractiveness of jobs. Note that this is a partial equilibrium result where the outside option of the worker is constant and equal to the economywide value of being unemployed. In general equilibrium, increased bargaining power for workers would decrease the value of being unemployed because of a fall in vacancies relative to searching workers.$^{28}$

**Robustness**

The model takes several shortcuts to facilitate the analysis and exposition, which might not be innocuous. Wages are assumed to be constant over all possible realizations of $x_t$. Typically, one would assume that wages change with flow costs, along with the profitability of a job. However, this is not generally the case if costs can move below the level at which jobs are created. One can show that there exists a notional cost level, call it $x_H$, with

$^{28}$No clear predictions arise from variation in the drift or variance in the process for flow costs.
If $x_H > x_C$, above which firms’ value of a vacancy is zero (or equal to the scrap value $D$). Costs are then so high that if bargaining broke down, firms would not replace a worker, but rather destroy the job. Hiring costs are not expected to be amortized. Between $x_H$ and the job destruction threshold $x_D$, the firms surplus, and thus the surplus of the match, would depend on $x_t$. Correspondingly, wages vary. In contrast, for flow costs below $x_H$, the surplus of the firm is given by $J(x_t) - V(x_t) = [rC + k]/q(\theta) + T(h)$, the replacement cost. This is constant if training is the same for all hires. If training varies depending on the expected duration of the job, lower flows costs would to some extent translate into wages. But the variation in wages would be much lower than that of flow costs. Since most workers would fall into this range of relatively invariant or even constant wages, the assumption of wages that are relatively constant is not as restrictive as it might seem.\textsuperscript{29}

The model imposes equality of the thresholds where a worker is fired and the job is destroyed. It may well be that a firm finds it profitable to fire a worker while keeping the job idle until costs (or generally market conditions) improve. At some point, it would try to fill the job again and resume production once a worker is found. Firing and job destruction thresholds would coincide only if costs of firing or the scrap value are high enough. The separation of these thresholds has an interesting implication for the sensitivity of job flows to variation in skill requirements. In contrast to the setup analysed here, exogenous training differences would indeed affect wages, but only slightly affect job flows. The reason is that the critical threshold for job destruction is barely affected by differences in training costs, which are match-related by not job-related. This casts doubt on an explanation of the relationship between wages and job flows in which higher firm-specific human capital creates long-run attachments between workers and firms, which drives down job flows (see Davis, Haltiwanger, and Schuh, 1996). With a separation of job destruction and firing, mainly worker flows would be affected.

\section{Conclusions}

The paper establishes a negative correlation between job flows and wage differentials across 3-digit U.S. manufacturing sectors. The empirical analysis shows that the correlation is not accounted for by industry characteristics that typically help explain the industry wage structure. However, jointly including firm size, capital-per-employee, and average education of the workforce in an industry renders the coefficient on job flows small and insignificant.

The labor market model developed to explain these findings features ex-ante job creation costs and endogenous training along with search and matching and endogenous job flows. The ex-ante nature of job creation costs allows to analyse the effects of job duration on wages. If these costs were ex-post, as in other search and matching models, they would by assumption be on the bargaining table and thus directly affect wages. Here, the effect is only indirect through job duration, which is inversely related to job reallocation rates. In the model with endogenous training, the industry structure of wages and job flows can

\textsuperscript{29}Formal derivation of this argument is available from the author upon request.
be explained by the fact that training responds to the differences in job duration that job creation costs bring about. One can think of factors that potentially amplify the response of wages to differences in job flows. For example, once workers are more productive through training, and thus more costly to replace, firms have an incentive to reduce costly turnover by offering higher wages.

How does this help interpreting the empirical findings? The role of job duration is most clearly understood for firm size. As reported in the introduction, Idson (1996) interprets his findings on the employer size wage effect by investments in firm-specific motivated by the security of long-run attachments that large employers can provide. It appears that the firm size-wage effect is an important factor in the industry structure of job flows and wages. While firm size plays no direct role in the model presented here, it also implies a causation from job duration to training and thus wages.

Capital intensity is likely to reflect the skill requirements for workers to operate complex machinery. In the model, this would be reflected by an exogenous variation in training, rather than the endogenous variation due to differences in expected job duration. To the extent that the regressions control for capital-per-employee, the analysis suggests that the remaining correlation between job flows and wages arises from the duration effect.

The role of average education in the wage regression can be interpreted as outlined in the introduction. If there are complementarities between skills and training, as in Neal (1998) then industries that require training will attract more able workers. The coefficient on average education would then proxy for the training provided in high wage industries. This is in line with the finding by Black and Lynch (1995) mentioned in the introduction that “employers who have hired workers with higher average education are more likely to train workers within their establishments.”

Other effects are possible however. If there are skill complementarities between workers, then workers will be more productive in industries that employ better workers.30 Even if there are no training investments, more stable industries will attract these better workers, and thus be able to enjoy these complementarities. An evaluation of this possibility is left to future research.

**Appendix**

**A Solution of the differential equations**

The expectational term in the Bellman equation for an active firm can be expressed as $E \left[ dJ_t \right] / dt = E \left[ dJ(x_t, h) \right] / dt = \mu x_t \partial J(x_t, h) / \partial x_t + \frac{1}{2} \sigma^2 x_t^2 \partial^2 J(x_t, h) / \partial x_t^2$, by Ito’s Lemma. Inserting and solving the resulting differential equations gives

$$J(x_t, h) = \frac{pf(h) - wc - k}{r} - \frac{1}{r - \mu} x_t - \frac{\alpha}{r - \mu} x_t^\alpha + B_j x_t^\beta$$

30See Kremer (1993).
31See, for example, Dixit and Pindyck (1994).
where $-\alpha < 0$ and $\beta > 0$ are the roots of the fundamental quadratic $\frac{1}{2}\sigma^2\gamma(\gamma - 1) + \mu \gamma - r$ associated with the differential equation and $A_J$ and $B_J$ are the constants of integration. Note that for the positive root ($\beta > 1$), $\partial \beta / \partial \sigma < 0$. The negative root can be eliminated by the boundary condition that $J(x_t, h)$ cannot go to infinity for $x_t \to 0$ so that $A_J = 0$. To determine $B_J$, one uses the optimality conditions that must hold at $x_D$. The value matching condition is $J(x_D, h) - D = 0$, and the smooth pasting condition is $\partial J(x_D, h) / \partial x_D = 0$. This gives $-1/(r - \mu) + \beta B_J x_D^{\beta - 1} = 0$. Solve for $B_J$ and insert into the value matching condition to get

$$\frac{P_f(h) - w_c - k}{r} - \frac{1}{r - \mu} \beta - 1 x_D - D = 0.$$ 

This equation can be rearranged to get $x_D$ as given in the text.

Similarly, one finds the solution of the wage equation, where $E [dW_t] / dt = E [dW(x_t)] / dt = \mu x_t W'(x_t) + \frac{1}{2} \sigma^2 x_t^2 W''(x_t)$. The solution is

$$W(x_t) = \frac{w_c}{r} + A_w x_t^{-\alpha} + B_w x_t^\beta,$$

with the same roots as above. The constant of integration $A_w$ can be eliminated by the same argument as before. Since the employment relationship ends when the job is destroyed, the value of employment must equal that of unemployment when $x_t = x_D$. Hence, $W(x_D) = w_c/r + B_w x_D^\beta = U$ or $B_w = (U - w_c/r)x_D^{-\beta}$. Inserting yields

$$W(x_t) = \frac{w_c}{r} + U - \frac{w_c}{r} x_D^{-\beta} x_t^\beta,$$

which can be rearranged to get the equation in the text.

## B Data construction

### Job creation and destruction

The job flow measures used in this study are taken from the data provided by the Center of Economic Studies at the U.S. Bureau of the Census. They can be downloaded from the website http://www.ces.usbc.gov. More details can be found in Davis, Haltiwanger, and Schuh (1996). They follow Davis and Haltiwanger (1990) and define job destruction and job creation rates in sector $s$ for period $t$ by

$$JC_{st} = \frac{\sum_{i=1}^{N_s} |X_{sit} - X_{sit-1}|^+ / Z_{st}}{s}$$

$$JD_{st} = \frac{\sum_{i=1}^{N_s} |X_{sit} - X_{sit-1}|^- / Z_{st}}{s}$$

where $X_{sit}$ is employment at establishment $i$ in industry $s$ at point in time $t$, and $Z_{st} = 0.5 \cdot (X_{st} + X_{st-1})$. $N_s$ denotes the number of firms in sector $s$. The first sum includes all positive changes whereas the second includes all reductions in employment. Net employment changes in a sector are simply given by $NET_{st} = JC_{st} - JD_{st}$. One can summarize the degree of turbulence in a sector by job reallocation ($JR$), which is the sum of destruction and creation. Excess job reallocation is a measure of the degree of job reallocation that goes beyond the amount necessary to accommodate net employment changes and is defined as

$$XJR_{st} = JR_{st} - |NET_{st}|.$$
**Profits-per-employee**

The computation of profits-per-employee follows a procedure suggested by Sanfey (1992) and used by Blanchflower, Oswald, and Sanfey (1996). They use the following formula, employing data from the NBER Productivity Database by Eric Bartelsman and Wayne Gray (see [www.nber.org](http://www.nber.org)).

\[
\pi = \frac{\text{value added} - \text{payroll}}{\text{CPI}} - \text{real depreciation} - \text{opportunity cost of capital}
\]

with

- real depreciation = \( \text{capital}_t - \text{capital}_{t+1} + \text{investment}_t \),
- opportunity cost of capital = \( \text{real interest rate} \times \text{real capital stock} \).

The real interest rate was taken to be the T-bill rate minus the inflation rate, and CPI is the consumer price index with the base year of the real variables, 1987. The CPI is contained in the March Files or can be taken with the T-bill rate from the International Financial Statistics of the IMF, for example.

**Classification of industries**

Note that most manufacturing industry codes (MIC) correspond to the CIC (1980) classification used for the Current Population survey up to 1992. Some industries had to be merged because they consisted of too few measurements in the wage data. All industries with less than twenty observations were merged to the next closest industry, so that no industry wage differential in any year has been estimated with less than 40 observations.
<table>
<thead>
<tr>
<th>MIC/CIC (CIC80)</th>
<th>CIC70</th>
<th>Description</th>
<th>SIC (1972)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>268</td>
<td>Meat products</td>
<td>201</td>
</tr>
<tr>
<td>101</td>
<td>269</td>
<td>Dairy products</td>
<td>202</td>
</tr>
<tr>
<td>102</td>
<td>278</td>
<td>Canned foods</td>
<td>203</td>
</tr>
<tr>
<td>110</td>
<td>279</td>
<td>Grain mill prod.</td>
<td>204</td>
</tr>
<tr>
<td>111</td>
<td>287</td>
<td>Bakery prod.</td>
<td>205</td>
</tr>
<tr>
<td>112</td>
<td>288</td>
<td>Confectionery</td>
<td>206</td>
</tr>
<tr>
<td>120</td>
<td>289</td>
<td>Beverage ind.</td>
<td>208</td>
</tr>
<tr>
<td>121</td>
<td>297</td>
<td>Misc. food</td>
<td>207, 209</td>
</tr>
<tr>
<td>130</td>
<td>299</td>
<td>Tobacco</td>
<td>211-214</td>
</tr>
<tr>
<td>132</td>
<td>307</td>
<td>Knitting mills</td>
<td>225</td>
</tr>
<tr>
<td>140</td>
<td>308</td>
<td>Dying &amp; finishing textiles, exc. wool &amp; knit goods</td>
<td>226</td>
</tr>
<tr>
<td>140/141</td>
<td>309</td>
<td>Floor coverings, exc. hard surface</td>
<td>227</td>
</tr>
<tr>
<td>142</td>
<td>317</td>
<td>Yarn, thread, and fabric mills</td>
<td>221-224, 228</td>
</tr>
<tr>
<td>140/150</td>
<td>318</td>
<td>Misc. textile mill products</td>
<td>229</td>
</tr>
<tr>
<td>151</td>
<td>319</td>
<td>Apparel and accessories</td>
<td>231-238</td>
</tr>
<tr>
<td>152</td>
<td>327</td>
<td>Misc. fabricated textile products</td>
<td>239</td>
</tr>
<tr>
<td>160</td>
<td>328</td>
<td>Pulp, paper, and paperboard mills</td>
<td>261-263, 266</td>
</tr>
<tr>
<td>161</td>
<td>329</td>
<td>Misc. paper and pulp products</td>
<td>264, 267</td>
</tr>
<tr>
<td>162</td>
<td>337</td>
<td>Paperboard containers and boxes</td>
<td>265</td>
</tr>
<tr>
<td>171</td>
<td>338</td>
<td>Newspaper publishing and printing</td>
<td>271</td>
</tr>
<tr>
<td>172</td>
<td>339</td>
<td>Printing, publishing, &amp; allied ind., exc. 338</td>
<td>272-279</td>
</tr>
<tr>
<td>180</td>
<td>348, 349</td>
<td>Plastics, synthetics, and resins; synthetic fibers</td>
<td>282</td>
</tr>
<tr>
<td>181</td>
<td>357</td>
<td>Drugs and medicines</td>
<td>283</td>
</tr>
<tr>
<td>182</td>
<td>358</td>
<td>Soaps and cosmetics</td>
<td>284</td>
</tr>
<tr>
<td>190</td>
<td>359</td>
<td>Paints, vanishes, and related products</td>
<td>285</td>
</tr>
<tr>
<td>191</td>
<td>367</td>
<td>Agricultural chemicals</td>
<td>287</td>
</tr>
<tr>
<td>192</td>
<td>347, 368</td>
<td>Industrial chemicals; misc. chemicals</td>
<td>281, 286, 289</td>
</tr>
<tr>
<td>200</td>
<td>377</td>
<td>Petroleum refining</td>
<td>291</td>
</tr>
<tr>
<td>MIC/CIC (CIC80)</td>
<td>CIC70</td>
<td>Description</td>
<td>SIC (1972)</td>
</tr>
<tr>
<td>-----------------</td>
<td>-------</td>
<td>------------------------------------------------------------------------------</td>
<td>------------</td>
</tr>
<tr>
<td>200/201</td>
<td>378</td>
<td>Misc. petroleum and coal products</td>
<td>295,299</td>
</tr>
<tr>
<td>211</td>
<td>379</td>
<td>Rubber products</td>
<td>301-306</td>
</tr>
<tr>
<td>212</td>
<td>387</td>
<td>Misc. plastic products</td>
<td>307,308</td>
</tr>
<tr>
<td>220</td>
<td>388</td>
<td>Tanned, curried, and finished leather</td>
<td>311</td>
</tr>
<tr>
<td>220/221</td>
<td>389</td>
<td>Footwear, except rubber</td>
<td>313,314</td>
</tr>
<tr>
<td>220/222</td>
<td>397</td>
<td>Leather products, exc. footwear</td>
<td>312,315-317,319</td>
</tr>
<tr>
<td>230</td>
<td>107</td>
<td>Logging</td>
<td>241</td>
</tr>
<tr>
<td>231</td>
<td>108</td>
<td>Sawmills, planing mills, and mill work</td>
<td>242,243</td>
</tr>
<tr>
<td>241</td>
<td>109</td>
<td>Misc. wood products</td>
<td>244,245,249</td>
</tr>
<tr>
<td>242</td>
<td>118</td>
<td>Furniture and fixtures</td>
<td>251-259</td>
</tr>
<tr>
<td>250</td>
<td>119</td>
<td>Glass and glass products</td>
<td>321-323</td>
</tr>
<tr>
<td>251</td>
<td>127</td>
<td>Cement and concrete, gypsum, and plaster products</td>
<td>324,327</td>
</tr>
<tr>
<td>262/252</td>
<td>128</td>
<td>Structural clay products</td>
<td>325</td>
</tr>
<tr>
<td>262/261</td>
<td>137</td>
<td>Pottery and related products</td>
<td>326</td>
</tr>
<tr>
<td>262</td>
<td>138</td>
<td>Misc. nonmetallic mineral and stone products</td>
<td>328,329</td>
</tr>
<tr>
<td>280</td>
<td>139,147-149</td>
<td>Metal industries (Steel, iron, aluminum, other)</td>
<td>331-339</td>
</tr>
<tr>
<td>281</td>
<td>157</td>
<td>Cutlery, handtools, and other hardware</td>
<td>342</td>
</tr>
<tr>
<td>282</td>
<td>158</td>
<td>Fabricated structural metal products</td>
<td>344</td>
</tr>
<tr>
<td>290</td>
<td>159</td>
<td>Screw machine products;</td>
<td>345</td>
</tr>
<tr>
<td>290/291</td>
<td>167</td>
<td>Metal stamping</td>
<td>346</td>
</tr>
<tr>
<td>300</td>
<td>168,258</td>
<td>Misc. fabricated metal prod.; ordnance</td>
<td>341,343,347-349</td>
</tr>
<tr>
<td>310</td>
<td>177</td>
<td>Engines and turbines</td>
<td>351</td>
</tr>
<tr>
<td>311</td>
<td>178</td>
<td>Farm machinery and equipment</td>
<td>352</td>
</tr>
<tr>
<td>312</td>
<td>179</td>
<td>Construction and material handling machines</td>
<td>353</td>
</tr>
<tr>
<td>320</td>
<td>187</td>
<td>Metalworking machines</td>
<td>354</td>
</tr>
<tr>
<td>331</td>
<td>188,189,197</td>
<td>Office &amp; accounting; elec. computing; machines</td>
<td>355-359</td>
</tr>
<tr>
<td>340</td>
<td>199</td>
<td>Household appliances</td>
<td>363</td>
</tr>
<tr>
<td>341</td>
<td>207</td>
<td>Radio, TV, and communication equipment</td>
<td>365,366</td>
</tr>
<tr>
<td>342</td>
<td>208</td>
<td>Electrical machine, equipment, and supplies, n.e.c.</td>
<td>361,362,364,367,369</td>
</tr>
<tr>
<td>351</td>
<td>219</td>
<td>Motor vehicles and motor vehicle equipment</td>
<td>371</td>
</tr>
<tr>
<td>352</td>
<td>227</td>
<td>Aircraft and parts</td>
<td>372,352</td>
</tr>
<tr>
<td>360</td>
<td>228</td>
<td>Ship and boat building and repairing</td>
<td>373</td>
</tr>
<tr>
<td>360/361</td>
<td>229</td>
<td>Railroad locomotives and equipment</td>
<td>374</td>
</tr>
<tr>
<td>370</td>
<td>238</td>
<td>Cycles and misc. transportation equipment</td>
<td>375,3799</td>
</tr>
<tr>
<td>370</td>
<td>237</td>
<td>Mobile dwellings and campers</td>
<td>3791</td>
</tr>
<tr>
<td>371</td>
<td>239</td>
<td>Scientific and controlling instruments</td>
<td>381,382</td>
</tr>
<tr>
<td>371</td>
<td>247</td>
<td>Optical and health services supplies</td>
<td>387</td>
</tr>
<tr>
<td>380</td>
<td>248</td>
<td>Photographic equipment and supplies;</td>
<td>386</td>
</tr>
<tr>
<td>380/381</td>
<td>249</td>
<td>Watches, clocks, and related devices</td>
<td>387</td>
</tr>
<tr>
<td>391</td>
<td>259</td>
<td>Misc. manufacturing industries</td>
<td>391-399</td>
</tr>
</tbody>
</table>
References


[16] Gibbons, Robert and Lawrence Katz (1992), Does Unmeasured Ability Explain Inter-

[17] Goux, Dominique, and Eric Maurin (1999), Persistence of Interindustry Wage Differ-
Economics* 17(3): 492-533.


Supply and Demand Factors, *Quarterly Journal of Economics* 107(1)

Journal of Economics*, 108

Structure, in: *Unemployment and the Structure of Labor Markets*, edited by Kevin Lang


[25] Leonard, Jonathan (1987), In the Wrong Place at the Wrong Time: The Extent of
Frictional and Structural Unemployment, in : *Unemployment and the Structure of Labor

[26] Mortensen, Dale, and Christopher Pissarides (1994), Job Creation and Destruction in

[27] Mortensen, Dale, and Christopher Pissarides (1999), Job reallocation, Employment fluc-
tuations, and Unemployment, in: John Taylor and Michael Woodford, eds, *Handbook of
Macroeconomics*, North-Holland

[28] Moulton, Brent (1986), Random Group Effects and the Precision of Regression Esti-

[29] Neal, Derek (1998), The Link between Ability and Specialization, *The Journal of Human
Resources*, 33(1)

MIT Press

[31] Sanfey, Peter (1992), *Insiders and Outsiders in Union models: Theory and Evidence for