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AND
THE CYCLICAL UPGRADING OF LABOR

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Abstract

We investigate whether a market-clearing model of the labor market is consistent with the cyclical upgrading of labor: workers tend to move to higher paying industries in expansions and to lower paying industries in contractions. By applying Roy's (1951) model of self-selection to industry fluctuations, we show that cyclical upgrading can be consistent with market clearing. Applying the model to inter-industry mobility patterns in panel data, we find evidence of substantial selection by comparative advantage. However, the panel data reveal a selection process that is inconsistent with cyclical upgrading. Thus the Roy model does not simultaneously account for inter-industry mobility in panel data and cyclical upgrading. The Roy model also fails to explain predictable patterns of wage changes for industry movers.

Inter-Industry Mobility and the Cyclical Upgrading of Labor

I. Introduction

Aggregate expansions are associated with upgrading in the labor market (Reder 1955; Okun 1973). In expansions, workers tend to flow from low wage industries such as retail trade to high wage industries such as durable-goods manufacturing. Indeed, employment in higher wage industries is more cyclically sensitive than employment in lower wage industries (Okun 1973; and Huizinga 1980). In addition, relative to the aggregate wage, wages do not rise in cyclical high-wage industries in expansions. Early research by Haddy and Tolles (1957) and Wachter (1970) concludes that inter-industry wage differences decline in expansions; and more recently Wood and Solon (1990) find that wages are equally procyclical in cyclical and noncyclical industries.

The evidence that employment is most cyclical in high wage industries and wages most procyclical in low wage industries has been cited to support disequilibrium or segmented markets theories of the labor market. First, the evidence appears to be inconsistent with a market-clearing equilibrium with high-wage cyclical industries exhibiting relatively large product demand increases in expansions: if the labor market clears, why would industries with large fluctuations in employment not have large fluctuations in wages? Second, as Okun (1973) stresses, if employers in high wage industries face queues of workers, then the industry need not increase its wage to expand employment: the upward slope of labor supply is irrelevant. Queues stabilize wages in high wage industries, but exacerbate movements in employment. McDonald and Solow (1985) draw essentially the same implications from a model where union bargaining in some industries is the source of industry wage effects and worker queues. Others draw similar conclusions from models that employ efficiency wages to create industry wage differences and queues (e.g., Akerlof and Yellen 1985).

The evidence of cyclical upgrading is not sufficient to support the conclusion of segmented labor markets. Market clearing does not require large movements in relative wages. First, if over the cycle inter-industry movers are low skill workers, then their transitions to high wage industries tend to bias down the wage growth in those industries. This is purely a compositional effect. Second, if high wage industries are more cyclically sensitive because they face quite elastic labor supply schedules, wages need not move much to support large flows of labor across industries.[1]

One of our purposes is to demonstrate that cyclical upgrading is consistent with a market-clearing equilibrium. A second purpose is to determine whether an equilibrium model can simultaneously account for other patterns of inter-industry mobility. To balance the analysis, we also apply a simple queuing model to inter-industry mobility.

After briefly documenting the industry employment and wage patterns, we develop a market-clearing model of self-selection to industries that accounts for the cyclical upgrading regularities. Heterogeneous workers follow comparative advantage in self-selecting into industries (Roy 1951). We characterize the distribution of skills that would be consistent with low wage workers moving to high wage industries in expansions. We contrast the predictions of the market-clearing model with predictions of a queuing model of the labor market: firms pay efficiency wages to attract higher quality applicants (e.g., Weiss 1980).

We use data from the Panel Study of Income Dynamics (PSID) to estimate the market-clearing selection model for twenty-five industries. Parameters of the selection process are estimated to be consistent with the wages of industry stayers and inter-industry movers in the United States. By comparing the wages of industry stayers, leavers, and entrants, we qualitatively identify the selection process. We find that comparative advantage lines up with absolute advantage in nearly all industries; thus each industry employs workers who are better *in that industry* than other workers would be. Although consistent with inter-industry mobility, this selection process is not consistent with cyclical upgrading.

The evidence of heterogeneity and comparative advantage suggests that industries face

[1] A third possibility is that labor contracts smooth the wages of senior workers. Although we do not explore wage smoothing in detail, we find evidence that workers with little or no seniority do *not* display more cyclically sensitive wages.

rising labor supply schedules that are more elastic in high-wage cyclical industries. Consistent with this result, we also find weak evidence that shadow prices of labor (i.e., true industry wage rates) in high-wage cyclical industries are less responsive to cyclical fluctuations in employment. However, the model fails to explain the wage changes of inter-industry movers: wages jump up (down) for entrants to (leavers from) high wage industries.

II. Industry Employment, Hours, and Wage Patterns

In this section, we document several industry employment, hours, and wage patterns for the United States. Which industries exhibit the biggest employment fluctuations and which have the biggest wage fluctuations? Are the cyclical employment and wage sensitivities correlated across industries? Do high wage industries fluctuate the most in terms of employment but the least in terms of wages? Briefly, does cyclical upgrading characterize industries in the United States?

To answer these questions, we analyze quarterly data on employment, weekly hours, and hourly wages in twenty-five industries from 1964 through 1987 from Bureau of Labor Statistics surveys of establishments. The first two columns of Table 1 display summary characteristics—averages over the sample period—of industry employment and wages for our twenty-five industries. Column 1 lists each industry's share of aggregate employment. Column 2 reports average hourly wages of production workers in each industry relative to average hourly wages in all private nonagricultural industries. Construction, Transportation, Utilities, and most manufacturing industries pay relatively high wages. The low wage industries include Textiles, Apparel, & Leather, Retail Trade, and most service industries.

To estimate the cyclical sensitivities of industry i's employment E_{it}, weekly hours H_{it}, and wages W_{it}, we regress each industry variable on aggregate employment E_t, our measure of the business cycle. In particular, let

$$\log(E_{it}/E_t) = a_i^e + \alpha_i^e t + \beta_i^e \log E_t + \epsilon_{it}^e \tag{1a}$$

TABLE 1

Cyclical Patterns Across Industries[a]
Establishment Data, 1964–1987

Industry	Employment Share (%)	Relative Wage	Elasticity of Relative[b]: Employment	Hours	Wages
Agriculture	4.3	0.63[c]	−0.13 (0.45)		
Mining	0.9	1.29	0.02 (0.66)	0.20 (0.21)	−0.28 (0.23)
Construction	4.7	1.53	1.59 (0.21)	0.20 (0.20)	−0.49 (0.10)
Metals	3.2	1.21	1.54 (0.19)	0.66 (0.11)	−0.04 (0.08)
Machinery	4.8	1.12	1.14 (0.19)	0.36 (0.07)	−0.24 (0.07)
Transportation Equipment	2.3	1.36	1.24 (0.41)	0.28 (0.23)	−0.05 (0.17)
Other Durables	3.4	0.96	1.02 (0.15)	0.17 (0.09)	−0.32 (0.06)
Food & Tobacco	2.2	1.00	−0.40 (0.13)	−0.02 (0.08)	−0.45 (0.08)
Textiles, Apparel, & Leather	3.0	0.73	0.50 (0.21)	0.13 (0.19)	−0.03 (0.09)
Paper, Printing, & Publishing	2.2	1.16	−0.10 (0.07)	0.21 (0.06)	−0.35 (0.05)
Chemicals, Petroleum, & Rubber	2.3	1.15	0.38 (0.14)	0.23 (0.07)	−0.46 (0.08)
Transportation	3.4	1.29	0.28 (0.12)	0.05 (0.08)	−0.16 (0.11)
Communications	1.4	1.22	−0.56 (0.44)	0.16 (0.21)	−0.33 (0.22)
Utilities	0.9	1.35	−0.74 (0.11)	−0.10 (0.09)	−0.35 (0.06)
Wholesale Trade	5.5	1.05	−0.25 (0.07)	−0.08 (0.05)	−0.21 (0.06)

TABLE 1–Continued

Industry	Employment Share (%)	Relative Wage	Elasticity of Relative[b]: Employment	Hours	Wages
Retail Trade	15.7	0.73	−0.46 (0.12)	−0.30 (0.07)	−0.10 (0.07)
Finance, Insurance, & Real Estate	5.2	0.92	−0.64 (0.05)	−0.14 (0.06)	−0.28 (0.08)
Business Services[d]	2.9	0.93	0.10 (0.13)	−0.43 (0.10)	−0.53 (0.10)
Repair Services	0.9	0.86[c]	0.10 (0.16)		
Personal Services	1.2	0.64[c]	0.12 (0.24)		
Entertainment & Recreation	1.0	0.89	−1.00 (0.33)	−0.09 (0.23)	0.94 (0.47)
Health Services	4.9	0.88	−1.07 (0.06)	−0.30 (0.09)	−0.40 (0.06)
Education	8.1	1.17[c]	−0.53 (0.18)		
Legal & Other Professional Services	6.0	1.01[c]	−0.47 (0.12)		
Public Administration	9.9	1.17[c]	−0.90 (0.11)		

[a]Standard errors are displayed in parentheses.

[b]These industry elasticities are measured relative to the aggregate elasticities, which are 0.22 (0.06) for hours and 0.08 (0.09) for real wages. By construction, the aggregate employment elasticity is 1.00.

[c]Establishment data are not available for wage rates and weekly hours. The relative industry wage is calculated from the PSID.

[d]For all service industries combined, relative hours per week display an elasticity of −.28 (standard error of .05) and relative wages an elasticity of −.04 (standard error of .07) with respect to movements in aggregate employment.

$$\log(H_{it}/H_t) = a_i^h + \alpha_i^h t + \beta_i^h \log E_t + \epsilon_{it}^h \tag{1b}$$

$$\log(W_{it}/W_t) = a_i^w + \alpha_i^w t + \beta_i^w \log E_t + \epsilon_{it}^w, \tag{1c}$$

where the variables without industry indices are aggregates. For each industry, we estimate the time-differenced analogues of the three equations. We report our estimates of β_i^e, β_i^h, and β_i^w, the three cyclical sensitivities, in columns 3–5 of Table 1.

We report the industry employment elasticity in column 3. Since our measure of the business cycle is aggregate employment, an industry with a constant share of aggregate employment over the business cycle receives a value of zero. Industries vary dramatically in their cyclical sensitivities. Construction and most durable manufacturing industries exhibit cyclical movements in employment that are more than twice the size of the aggregate fluctuations. Utilities, Public Administration, and many service industries exhibit cyclical movements in employment that are considerably less than half the size of aggregate movements.

Reflecting the cyclical upgrading of labor across industries, the cyclical sensitivities of industry employment are positively correlated with industry wages. The correlation between industry relative wages in column 2 and the industry employment elasticities in column 3 is .32. High wage industries expand more in aggregate expansions.

Cyclical movements in industry workweeks are summarized in column 4. Data on the workweek, hours per worker per week, are available only for production workers. In the aggregate, workweeks are procyclical: a one percent increase in aggregate employment is associated with an increase in hours per week of 0.22 percent. In almost all cases, industries with procyclical shares of employment also have sharp increases in hours per week. These relative movements are large and statistically significant in a number of cases. The correlation between the industry employment and hours elasticities is .72. Furthermore, like employment, the workweek is more cyclical in high wage industries. The correlation between industry relative wages in column 2 and industry hours elasticities in column 3 is .52.

Column 5 presents the estimated cyclical sensitivities of industry wages relative to aggregate wages in the private nonagricultural economy. (Wages are average hourly earnings for production workers; we use the GNP Deflator to compute real wages.) Aggregate real wages are slightly procyclical over the period 1964 to 1987: a one percent increase in aggregate employment is associated with a 0.08 percent increase in real wages. In expansions average industry wages fall relative to average aggregate wages, so industry wages tend to move countercyclically relative to aggregate wages. Because expansions are associated with faster employment growth in high wage industries, aggregate wages vary procyclically relative to a weighted average of industry wages. In response to a one percent increase in aggregate employment, aggregate wages increase by 0.23 percent relative to the average response across the industries, which weights industries by their long-run employment shares. Huizinga (1980) also documents this disparity between aggregate and industry wage movements, but at the one-digit industry level.

Although the relationships are fairly weak, high wage and cyclically sensitive industries have the least procyclical wages. First, the cyclical sensitivity of industry wages is negatively correlated with the level of industry wages: the correlation between industry wage elasticities in column 5 and industry wages in column 2 is $-.27$. Second, industries with the most procyclical employments have the least procyclical wages: the correlation between industry employment and wage elasticities is $-.17$. The weakness of these relationships is consistent with Wood and Solon's (1990) finding that the inter-industry wage structure is largely unrelated to the business cycle.

The establishment data reveal four patterns in industry employment, hours, and wages: (a) high wage industries tend to be more cyclically sensitive; (b) across industries, fluctuations in the workweek mimic employment fluctuations; (c) relative to aggregate wages, industry wages move countercyclically; (d) industry wages are not more procyclical in high-wage, cyclically sensitive industries.

III. Economic Hypotheses

Despite their richness, many of the industry employment and wage regularities are consistent with both segmented-market and market-clearing approaches to the labor market. With a segmented labor market, the source of the regularities is queues for jobs in high wage industries. Employment in high wage industries fluctuates more because firms in these industries draw from the queue without raising wages. Hence industries with high wages and large employment fluctuations are predicted to have small wage fluctuations. Since workers drawn from the queue receive a jump in pay, aggregate wages would appear to be procyclical even if industry wages were not cyclical. Thus regularities (a), (c), and (d) are consistent with segmented labor markets. However, with a queue for employment in the high wage industries, it is not obvious why workweeks in these industries would rise in expansions.

With heterogeneous workers and market clearing, self-selection can produce many of the industry employment and wage regularities. The close link between employment and hours suggests an increasing supply price of labor, which can be generated by sorting heterogeneous workers by comparative advantage. If high wage industries are the most cyclical, then a cyclical expansion could draw the most talented workers from low wage industries and these workers could be the least talented workers in the high wage industries. Such inter-industry mobility generates a countercyclical selection bias in industry wages, which captures regularity (c). Industries that do not fluctuate do not have this countercyclical bias, which might account for regularity (d).

To be more precise in sorting among the competing hypotheses, in this section we sketch an equilibrium model of selection and investigate whether any inadequacies of the model can be remedied by introducing queues.

Roy's Model of Self-Selection

We use Roy's (1951) equilibrium model of self-selection in the labor market to analyze the effects of aggregate fluctuations that shift industry demands for labor. Shifts in industry labor demands generate changes in the composition of employment, production, and consumption that are supported by changes in industry wage rates and product prices. The induced reallocation of labor produces compositional effects that are potentially consistent with the industry wage and employment regularities.

We begin by summarizing the essential features of the selection model. There are $n+1$ industries indexed by $i = 0,\dots,n$. Industry 0 is the nonmarket or home sector, which we treat the same as any industry in the market. Each industry faces a downward-sloping demand for its product. Each industry's output is an increasing concave function of its labor input L_{it}: $q_{it} = F_{it}(L_{it})$. There is a large number of *identical* firms within each industry. Taking industry product prices $\boldsymbol{p}_t = (p_{1t},\dots,p_{nt})$ and wage rates $\boldsymbol{\omega}_t = (\omega_{1t},\dots,\omega_{nt})$ as given, firms behave competitively in both product and labor markets. From competition, industry employment satisfies $p_{it}F'_{it} = \omega_{it}$.

There is a large number of *heterogeneous* individuals. Skills vary across workers, and these skills are valued differently in different industries. If employed in industry i, an individual worker generates x_i units of labor input. (So L_i aggregates the x_i over workers employed in industry i.) At time t, the wages (or wage income) of a worker in industry i is $W_{it} \equiv \omega_{it}x_i$. Individuals choose where to work by comparing wages across industries, each accepting his highest offer. We indicate the choice by an industry variable I_t; I_t equals i if the individual works in industry i.

In the competitive equilibrium, product prices $\boldsymbol{p}_t^* = (p_{1t}^*,\dots,p_{nt}^*)$ clear the product market, wage rates $\boldsymbol{\omega}_t^* = (\omega_{1t}^*,\dots,\omega_{nt}^*)$ clear the labor market, and workers follow comparative advantage in self-selecting across industries. (Given heterogeneity, wage rates need not equalize across industries.) If comparative advantage lines up with absolute advantage, each industry employs workers who are better than average in that industry. Otherwise, each industry specializes in a quality of labor, and industries are naturally ordered from least to most selective.

The case of two ordered industries is illustrated in Figure 1. With each worker described by a point on the graph, the iso-probability contours reflect the distribution of skills in the population. For workers "located" along the ray from the origin, wage income is equalized across the two industries. Thus the ray with slope w_{1t}/w_{2t} is the reservation wage line. Workers below the reservation wage line sort into industry 1; those above choose industry 2. As drawn, the wages of workers employed in industry 1 are high because industry 1 attracts the higher quality workers (i.e., positive selection); average wages in industry 2 are low because the workers who sort into industry 2 are lower quality (i.e., negative selection).

Aggregate fluctuations—through technology shocks or product demand shocks—generate shifts in industry labor demands. In a cyclical expansion, the nonmarket sector declines, some industries grow faster than others, industry wage rates fluctuate, and workers re-sort across industries. Consistent with the simplest economic principles, industry employment and wage fluctuations depend on the magnitude of the shift in industry labor demand and the elasticity of labor supply. For instance, if industry labor supply curves have different slopes, workers re-sort across industries in response to a technology shock that increases the marginal product of labor k percent in all industries. An industry with elastic labor supply can draw from many marginal workers willing to work in the industry for only a small increase in the industry wage rate. Employment in such an industry grows with little increase in the industry wage rate. An industry with few marginal workers grows little, but the industry wage rate must rise to attract even these few extra workers. Consequently, an aggregate expansion that is neutral in terms of industry labor demands shifts employment toward industries with elastic labor supplies.

The selection model can account for several of the industry employment and wage regularities. Begin by assuming that industries are ordered by the degree of selection, with the most selective industries attracting the best workers. (This is illustrated in Figure 1.) Two of the many industries are construction, with high wages and cyclically sensitive employment, and retail trade, with low wages and cyclically less-sensitive employment. Within the context of the selection model, wages are high in construction as a result of

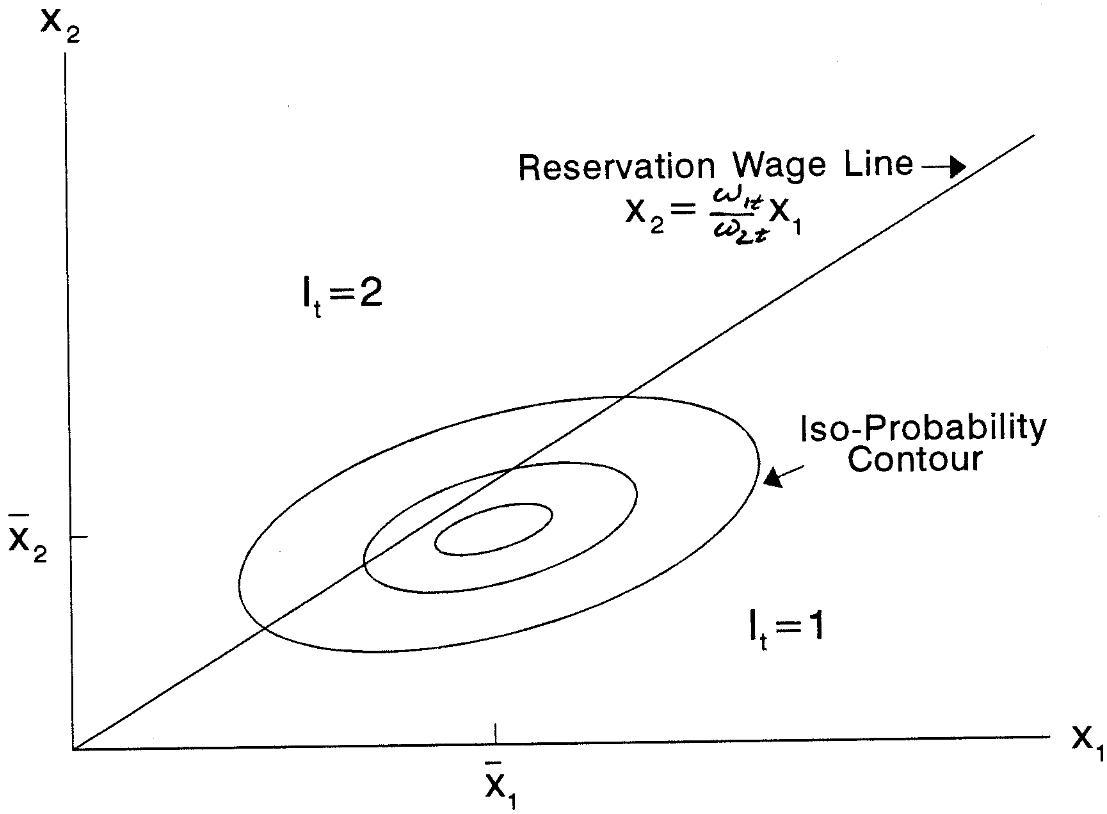

Figure 1: Industry Selection in the Roy Model

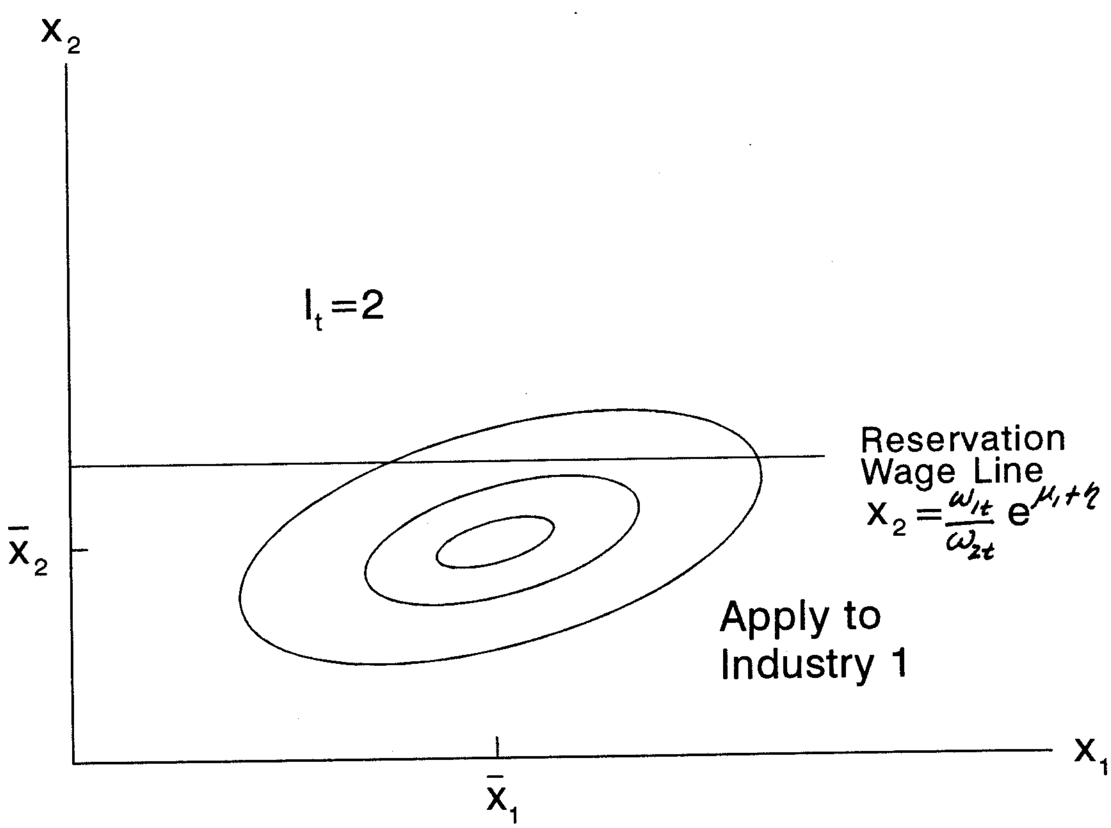

Figure 2: Industry Selection with Queuing

positive selection, which raises the average quality of labor above construction's population mean; negative selection in retail trade lowers wages there. Consider a cyclical expansion that increases all the industry wage rates ω_t, but some more than others, with employment in construction growing more than employment in retail trade. Among the many inter-industry flows, some workers flow from retail trade to construction. The new hires in construction tend to dilute the average quality of construction workers, which attenuates the wage increase in construction. These low-quality new hires in construction were high-quality retailers. As its best workers exit, retail trade's average quality of labor falls, which depresses wage growth in retailing. Re-sorting across industries attenuates industry wage growth in expansions.

In contrast, inter-industry mobility does not bias aggregate wages—an employment-weighted average of the industry wage rates—down in an expansion. The wages of stayers in each industry grow at the same rate as the industry's wage rate. Revealed preference implies that the wages of an inter-industry mover grow at least as fast as the wage rate grows in the industry he leaves. Therefore, self-selection across industries in expansions reinforces the upward force on aggregate wages. However, self-selection attenuates the downward force on aggregate wages in contractions: mobile workers escape from industries with the deepest wage cuts. Overall, aggregate wages reflect a procyclical bias in expansions and a countercyclical bias in contractions as a result of inter-industry mobility.[2] This asymmetry could be misinterpreted as a downward rigidity of wages.

Our application of Roy's selection model illustrates that, with ordered industries, self-selection generates patterns consistent with the industry employment and wage patterns documented in section II. If industries with high wages are more cyclically sensitive, workers move from industries with low wages to industries with high wages; the inter-

[2]This contrasts with Heckman and Sedlacek's (1985, 1107–10) conclusion that self-selection across sectors within the labor market reinforces the variability of aggregate wages. If their simulations are correct, self-selection based on non-wage attributes—rather than self-selection across sectors—must account for their results. We consider this below.

industry movers receive higher wage growth in the transition than their former co-workers who remain employed in the industry with low wages; and relative to aggregate wages, industry wages are countercyclically biased.

The ability of the Roy model to account for cyclical upgrading hinges on the assumptions that industries are ordered and high wage industries are cyclically sensitive. For instance, if each industry were characterized by positive selection, which would occur if the probability contours in Figure 1 were negatively sloped, self-selection would not generate all the regularities of cyclical upgrading. As employment fluctuates across industries, the worst workers from one industry would become the worst workers in another. As a result, industry wages in the least cyclical industries would be procyclically biased: these industries would lose their low quality workers in expansions, and the low quality workers would return in contractions. The evidence of cyclical upgrading in Table 1 does not support this.

Is there evidence regarding the selection process and the ordering of industries? Are the industries with negative selection cyclically less sensitive? Does the model yield strong testable predictions? By comparing the wages and wage changes of industry stayers and inter-industry movers in panel data, we can determine whether the estimated selection process is consistent with cyclical upgrading and search for violations of the model's restrictions.

Empirical Specification

In this subsection, we sketch our methods for using panel data to address these issues. We have three methods. The first compares the wages of industry stayers and inter-industry movers; the second computes the wage changes of industry stayers; and the third compares the wage changes of industry stayers and inter-industry movers.

Following the long tradition in labor economics, we analyze log wages. An industry's offer of wages (in logs) is the sum of its shadow price of labor (in logs), the industry's population mean of labor input and a random variable.

$$\log W_{it} = \log \omega^*_{it} + \log x_i \tag{2}$$

$$= \log \omega_{it}^{*} + \mu_i + \epsilon_i,$$

where the random vector $\log \boldsymbol{x} = (\log x_0, \ldots, \log x_n)$ has mean $\boldsymbol{\mu} = (\mu_0, \ldots, \mu_n)$ and covariance matrix Σ.[3]

Our first method compares the wages of industry stayers with the wages of new hires, the entrants into the industry. By positioning inter-industry movers in the distributions of wages in their former and new industries, we can determine whether each industry is characterized by positive or negative selection. Suppose a worker moves from industry 2 to industry 1. By comparing his wages in industry 1 with average wages of workers who remain in industry 1, we establish whether the new hire is a below- or above-average worker in his new industry. If the new hire is below average, then industry 1 exhibits positive selection. (Steepening the ray in Figure 1 would produce this result). If the new hires are above average, then industry 1 exhibits negative selection.

By comparing the mover's wages before he left industry 2 with the average wages of subsequent stayers in industry 2, we can determine whether industry 2 is characterized by positive or negative selection. If the mover was below average, industry 2 exhibits positive selection; it retains its best workers as the worst workers leave. If the mover was above average in his former industry, that industry exhibits negative selection; its best workers are the first to go.

More formally, let W_{τ}^{ij} denote average *log* wages at time τ of workers employed in industry i at time t and industry j at time $t+1$. For example, W_t^{11} is the average of log wages at time t of workers who stay employed in industry 1 at times t and $t+1$; and W_t^{21} is the average of log wages at time t of workers employed in industry 2 who subsequently move to industry 1. If industry 1 grows, the following wage comparisons qualitatively identify the

[3]Skills are invariant to time. Unfortunately, this rules out accumulation of industry-specific skills.

selection process:

$$W_{t+1}^{11} - W_{t+1}^{21} \gtrless 0 \tag{3a}$$

$$W_{t}^{22} - W_{t}^{21} \gtrless 0. \tag{3b}$$

If the first expression is positive (negative), industry 1 exhibits positive (negative) selection, because the entrants are below- (above-) average workers. If the second expression is positive (negative), there is positive (negative) selection to industry 2; the leavers were below- (above-) average workers in the industry they left.

If industry 2 grows, so some individuals move from industry 1 to industry 2, we can identify the selection process with the following wage comparisons:

$$W_{t+1}^{22} - W_{t+1}^{12} \gtrless 0 \tag{4a}$$

$$W_{t}^{11} - W_{t}^{12} \gtrless 0. \tag{4b}$$

Therefore, if industries periodically expand and contract, these simple computations of average industry log wages yield two sets of estimates of the selection process.

Our second method computes the wage *changes* of the industry stayers to identify the growth rate of each industry's wage rate. (The size of the wage change of stayers reveals nothing about the selection process: a large wage change is consistent with positive or negative selection in either industry.) Time differencing the average log wages of the industry stayers yields the growth rate of the industry's shadow price of labor.

$$W_{t+1}^{11} - W_{t}^{11} = \log \omega_{1,t+1}^{*} - \log \omega_{1t}^{*} \equiv \gamma_{1t} \tag{5a}$$

$$W_{t+1}^{22} - W_{t}^{22} = \log \omega_{2,t+1}^{*} - \log \omega_{2t}^{*} \equiv \gamma_{2t}. \tag{5b}$$

This enables us to characterize the evolution of industry wage rates without compositional biases. However, the result does depend on the time-invariance of skills, so mobility does not exploit transitory fluctuations in labor input to industries (Keane, et al. 1988).

Our third method detects patterns of wage changes that are inconsistent with the selection model. Equilibrium self-selection imposes inequality restrictions on the wage changes of inter-industry movers. For illustration, consider movers from source industry i to target industry j. If the wage growth of movers were less than the wage growth of their former co-workers who remain in industry i, why would the movers choose to move? Would the turnover be involuntary? Likewise, if the wage growth of the entrants to industry j were to exceed the wage growth of the old hires (i.e., target industry stayers), we would wonder why the entrants did not choose to be employed in industry j at time t. Were they prevented from entering industry j? Is there a queue for jobs in industry j?

We formalize these ideas with the following proposition:

PROPOSITION: If workers sort across industries on the basis of current wages, then the wage growth of movers from industry i to industry j must be greater than the wage growth of stayers in the movers' source industry (i) and less than the wage growth of stayers in the movers' target industry (j). That is,

$$\Delta W^{ii} < \Delta W^{ij} < \Delta W^{jj}. \tag{6}$$

PROOF: Available on request.

Armed with this result, we can search for violations of the inequalities by computing average wage growth within and between each industry pair. The proposition can be be tested less formally with a simple regression. In section V, we regress the wage growth of each inter-industry mover on the average wage growth in his source industry, ΔW^{ii}, and the average wage growth in his target industry, ΔW^{jj}. To satisfy the inequality restrictions, industry-specific intercepts must be zero, and the two industry wage-growth coefficients must be positive and sum to less than one.

Compensating Differentials and Career Dynamics

Although the proposition holds for any number of industries and any distribution of skills, it does contain an important qualification: workers sort across industries in period t on the basis of wage offers in period t. If jobs were characterized by attributes, as well as wages, then the restrictions on the growth rates could be violated even though the labor market efficiently allocates workers to industries. If job attributes differ across industries, then a worker who would be indifferent between two industries would not have the same wage offer from the two. The compensating wage differential drives a wedge between the wage offers faced by a marginal worker. Bringing the marginal worker into the industry with low amenities and high wages leads to a jump in his pay. If the marginal worker leaves this industry, his pay jumps down. These jumps can violate the proposition.[4]

The proposition could also be violated if industry selection depends on dynamic elements, such as accumulating or learning of industry-specific skills. With career dynamics, future prospects in an industry affect the reservation wage for selection into that industry, which drives a wedge between the wage offers faced by a marginal worker.[5] As with compensating wage differentials, these wedges could violate the proposition. But with career dynamics, the industry-specific values of future prospects vary over a worker's career, vanishing at retirement. If career dynamics is the source of violations of the proposition, violations should be less frequent for older workers.

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[4]One might reasonably conjecture that a second qualification is important: the wages of a worker equal the shadow value of his labor. However, the proposition and its implications survive relaxing this restriction. If a workers' wages in industry i are a convex combination of the shadow values of his labor in industries i and j, the wage growth of inter-industry movers must be bounded by the wage growths of stayers in the two industries. Therefore, if violations of the proposition are detected, the evidence could not be accommodated by such a rent sharing scheme.

[5]Suppose skills $\boldsymbol{x}_t = (x_{0t}, \ldots, x_{nt})$ follow a stochastic law of motion that depends on the history of selected industries. Let $V_t(\boldsymbol{x}_t) = \max_{I_t}\left\{W_{I_t} + \mathrm{E}_t V_{t+1}(\boldsymbol{x}_{t+1})\right\}$ denote a worker's expected present value of wage income. He selects industry i if, for all $j \neq i$, $W_{it} > W_{jt} + \mathrm{E}_t\left\{V_{t+1}(\boldsymbol{x}_{t+1} \mid I_t = j) - V_{t+1}(\boldsymbol{x}_{t+1} \mid I_t = i)\right\} \equiv W_{jt} + Z_t$. The term Z_t fully summarizes how a worker's current selection of industry affects future prospects. If industry i has relatively good prospects for wage growth, Z_t would be negative: a worker rejects better wage offers to work in industry i.

Efficiency Wages

Several economists have suggested that high-wage cyclical industries face queues of willing and able workers. In the Roy model, workers select industries on the basis of wage payments that reflect marginal products. Of course, factors other than comparative advantage might influence the allocation of labor to industries. A lesson from the Roy model is that sorting on the basis of comparative advantage generates rising supply prices. Consequently, to capture the absence of wage increases with queues for industry employment, rationing must interfere with comparative advantage. Extending the Roy model to include queues for employment in high wage industries is one way to distort comparative advantage. Here we outline an efficiency wage model.

The efficiency wage model in Weiss (1980) is a natural extension of the Roy model. Consider the case of two industries. In industry 1, the efficiency wage industry, the random component of labor quality ϵ_1 is not observed by firms even after production. Firms in industry 2 accurately measure each worker's labor quality, so wage offers in industry 2 follow equation (2) above. Without knowledge of ϵ_1, competition among firms in industry 1 yields wage offers

$$\log W_{1t} = \log \omega_{1t} + \mu_1 + \eta, \tag{7}$$

where η is the efficiency wage premium. Observable differences in labor quality, reflected in μ_1, allow for variation in wages across workers in industry 1.

A worker applies for employment in industry 1 if his wages there would exceed his wages in industry 2. Because wages in industry 1 do not depend on individual skills, the reservation wage is horizontal line in Figure 2. Workers above the reservation wage line select industry 2; those below the line *apply* to industry 1. Formally, a worker applies to industry 1 if and only if

$$\epsilon_2 < \eta + (\log \omega_{1t} - \log \omega_{2t}) + (\mu_1 - \mu_2). \tag{8}$$

Applicants to industry 1 tend to have low skills in industry 2, and the average quality of workers in industry 2 increases with the wage premium η. If and only if ϵ_1 and ϵ_2 are positively correlated, quality in the efficiency wage industry also increases with η. Although this condition is necessary for firms to pay efficiency wages, our stayer-mover wage comparisons cannot detect the correlation: wages in efficiency wage industries do not reflect ϵ_1.

Not knowing the quality of any applicant, each firm in industry 1 chooses a wage premium to minimize labor cost. Firms lower labor cost by raising the wage provided the higher wage attracts a sufficiently higher-skilled pool of applicants. This produces an efficiency wage premium, with employment rationed in industry 1. Firms have no incentive to cut wages in the face of queues; and workers cannot gain employment by offering to work for less than the efficiency wage. Although the efficiency wage premium raises the wage in industry 1, the efficiency wage need not exceed the average wage in industry 2; indeed, self-selection is a force toward higher average wages outside the efficiency wage industry.

Consider the effect of an increase in industry 1's demand for labor. With no shift in the distribution of worker skills, the efficiency wage remains unchanged. Firms in industry 1 employ a greater proportion of job applicants. Thus shifts in employment imply no relative wage movements. Up to the point where rationing ceases, industry 1 appears to face a perfectly elastic supply of labor.[6]

Compared with market clearing, efficiency wages with queuing carries different predictions for the wage changes of inter-industry movers. With market clearing, the wage

[6]Union bargaining also generates queuing. The number of workers willing to work in industry 1 increases with the union wage premium, but the quantity demanded of union labor decreases. This produces a queue of workers. If unionized firms randomly chose applicants from the queue, union workers and applicants would look similar. As with efficiency wages, the industry effectively would face a perfectly elastic supply of workers. However, it would be more efficient for unionized firms to select workers on the basis of comparative advantage. We emphasize the efficiency-wage model because, by interfering with comparative advantage, it contrasts most sharply with the Roy model.

changes of inter-industry movers are distributed between the wage change of industry 2 stayers and the wage change of industry 1 stayers. With a small flow of inter-industry movers (so the entrants are marginal), the variance of their wage changes would be small. Furthermore, for industry movers, their wages in the source industry would be an excellent predictor of their wages in the target industry.

By contrast, the efficiency-wage model predicts sizable wage changes for movers: entrants into the efficiency wage industry capture the wage premium; leavers lose the premium. Since the size of the rents varies across workers, the efficiency-wage model predicts a larger variance of mover's wage changes. Because wages in the efficiency wage industry do not depend on the individual's skill, a mover's pre-move wage in a low wage industry would poorly predict his post-move wage in a high-wage, cyclically sensitive industry. However, inter-industry movers outside the efficiency wage sector should have strong predictive power of pre-move wages. Even with compensating differentials, pre-move wages should be a strong predictor of post-move wages because movers are marginal. So this test allows us to discriminate between compensating differentials and efficiency wages.

A final test allows us to discriminate between career dynamics and efficiency wages. If industry wage effects are less important for the old, we would have some evidence of career dynamics, but it could be age-varying efficiency wages: if skills are revealed or quit rates decline over a worker's career, firms in the efficiency wage sector would not pay an efficiency wage to old workers. Nevertheless, we can discriminate between the two hypotheses. With career dynamics, we expect entrants to accept a low wage in retail trade in exchange for retail trade's high value of future prospects. Are separation rates low in retail trade? Is stayers' wage growth in retail trade relatively high? That is, industry wage effects are predicted to be negatively correlated with industry retention rates and industry stayers' wage growth rates. These correlations are not predicted by efficiency wages, even age-varying efficiency wages.

IV. Data

Ideally, data for estimating the industry selection model would include six features. First, since we seek to estimate parameters for the U.S. labor market, the sample should be representative of the working age population of the United States. Second, since we analyze movers from industry i to industry j, which in any year is a small fraction of the population, we need a large data set. Third, since our estimators compare wages before and after industry changes, individuals must be surveyed at least twice. Fourth, to address aggregate fluctuations, the data should extend over a fairly long period. Fifth, individuals should report pay and industry of employer at the time of the interview rather than over a protracted period. Sixth, the data should include the usual set of supplementary variables.

Recognizing that no publicly available data set satisfies all these features, we selected the Panel Study of Income Dynamics (PSID) on the basis of its advantages and our ability to cope with its disadvantages. Beginning in 1968, the PSID is an ongoing twenty-year panel of nearly 7,000 households. Industry data have been reported since 1971. This leaves seventeen years of data to uncover the effects of aggregate fluctuations on inter-industry mobility. The PSID includes annual observations covering survey week pay with the main employer, the employer's industry, as well as earnings, weeks, usual hours per week last year. It also includes a large set of supplementary variables, however some variables are not available in all years of the panel.

For our purposes, the PSID also has deficiencies.[7] Because the PSID studies families, most of the information concerns the household's head. Although some information on spouses is surveyed, these data are not as rich as the household head's. For instance, spouse's survey week responses are collected in only two years in the 1970s. For our purposes, the PSID is also small. Although we might start with nearly 150,000 individual-

[7]We also considered using the the matched sample of the Current Population Survey and the National Longitudinal Surveys. Although the matched CPS is large, it is address based. Therefore, the matched sample loses inter-industry movers who change addresses. None of the NLSs provides the full range of ages.

year observations on the working age population, annual transitions among narrowly classified industries produce many unacceptably small cell sizes. To remedy this, we analyze twenty-five industries plus nonemployment.

Overall, our sample from the PSID includes detailed information on the mobility across twenty-six industries of a representative sample of household heads and spouses in a short panel from 1979 through 1987. Where using a longer panel is essential, we limit the sample to household heads (males and females) to extend the sample period back to 1971.

In addition to the PSID's stratified random subsample, we include a subset of the smaller nonrandom (Survey of Economic Opportunity) subsample. Rather than discarding the entire nonrandom sample, we randomly select observations such that the distribution of wages in our subset of the nonrandom sample mimics the wage distribution in the random sample. In short, we oversample high wage heads and spouses to undo the original undersampling. This allows us to keep about half of the nonrandom sample. After excluding self-employed persons, we are left with a sample of 35,418 observations on household heads and 23,413 observations on spouses covering the years 1979 through 1987.

Two key variables in our analysis are industry indicators and wage rates. Industry turnover compares reported industry of employment at one survey date to the reported industry at the survey the following year. Many of the workers who change industry classification from one year to the next appear to remain with the same employer. We treat persons with changing industry codes as true industry changers only if they report changing employers during the year.

Our measure of wages uses the respondent's report of his survey week pay on his main job. For salaried workers, we divide salary by annual hours worked during the survey year. Our wage variable is inflated to 1987 dollars using the Current Population Surveys' series on average hourly rate of pay for wage and salary workers.[8]

We treat the nonmarket sector (i.e., unemployment or out of the labor force) as an industry like any other. Unfortunately, we do not observe the wage rate—the value of time out of the labor market—for the nonmarket sector. We take two approaches to this deficiency. One is to ignore the nonmarket sector to estimate the mover-stayer wage comparisons as if all workers are always employed. (The nonmarket sector does not present a problem for our analysis of the wage changes of industry stayers or our analysis of the wage changes of inter-industry movers.) We also impute wages for workers in the nonmarket sector. Almost all individuals participate in the labor market at some time. With a lengthy panel data set, we can use reported market wages in previous and future years to impute a value at home. We use the lowest value of the wage to proxy for the individual's value at home.[9] This might be an error-ridden measure for any particular individual. But we expect this to be less problematic for our estimators, which rely on within-industry *averages* of wages and wage changes.

Summary statistics for our sample using survey years 1979 to 1987 are displayed in Tables 2 and 3. The distribution of workers across industries is fairly consistent with the aggregate establishment numbers reported in Table 1. (Employment shares in Table 3 are expressed relative to both market and nonmarket sectors.) Our sample has a considerably smaller fraction in Agriculture and a considerably higher fraction in Personal Services. Only thirty-three percent of our sample is out of the work force; whereas, the fraction for the aggregate economy is nearly forty percent. This probably reflects the disproportionate number of household heads in our sample relative to the U.S. population.

Table 3 provides means and standard deviations of log wage rates by industry. Relative industry wages are fairly similar to those from establishment data reported in Table 1. Entertainment & Recreation, which is a somewhat low wage industry in the

[8]In some years a few of the very highest wage rates were top coded. We reset these top-coded wages using labor earnings divided by annual hours of work. Also, we treat any wages below \$2.50 or above \$100.00 (1987 \$) as outliers and set the wage to missing.

[9]About forty percent of the nonmarket individual-year observations never report a wage, so we cannot impute an implicit nonmarket wage. Given that we never observe these individuals with jobs, they are likely to be irrelevant for calculating the response of industry employments to reasonable variation in industry wage rates.

TABLE 2

Summary Statistics
Panel Study of Income Dynamics, 1979–1987

Variable	Mean	Standard Deviation	Number of Observations
Real Hourly Rate of Pay (1987 $)	10.90	7.37	34,528
Real Annual Earnings Last Year (1987 $)	17,798	15,413	51,269
Real Hourly Earnings Last Year (1987 $)	11.57	7.06	43,066
Weeks Worked Last Year	36.49	18.54	53,081
Weekly Hours Worked Last Year	33.89	17.20	52,941
Annual Hours Worked Last Year	1,410	978	58,831
Government Employee	0.22	0.42	40,765
Union	0.29	0.45	31,416
Tenure with Employer, Months[a]	87.99	91.43	32,611
Separated from Employer	0.26	0.45	45,279
Experience, Years	16.08	11.41	51,120
Age	38.77	13.55	58,831
Schooling	12.39	2.71	58,372
Male	0.45	0.50	58,831
White	0.73	0.44	58,682
Disabled	0.15	0.36	53,930
Married	0.78	0.41	58,831
Number of Children in Household	1.09	1.23	58,831
SMSA	0.61	0.48	58,549
Household Head	0.60	0.49	58,831

[a]Tenure with employer is based on survey years 1981–1987.

TABLE 3

Industry Summary Statistics
Panel Study of Income Dynamics, 1979–1987[a]

Industry	Employment Share (%)	Log Wage[b] Mean	Log Wage[b] Standard Deviation	Log-Wage Residuals[c] Mean	Log-Wage Residuals[c] Standard Deviation
Nonmarket	33.0				
Agriculture	0.8	−.476	.502	−.366	.442
Mining	0.6	.195	.433	.175	.367
Construction	3.3	.099	.459	.080	.395
Metals	1.6	.119	.378	.084	.325
Machinery	3.7	.154	.453	.096	.335
Transportation Equipment	2.5	.286	.389	.217	.321
Other Durables	2.3	−.032	.463	−.013	.348
Food & Tobacco	1.3	.019	.447	.049	.377
Textiles, Apparel, & Leather	1.8	−.456	.372	−.139	.325
Paper, Printing, & Publishing	1.6	.066	.492	.031	.358
Chemicals, Petroleum, & Rubber	1.7	.201	.442	.133	.348
Transportation	3.0	.210	.468	.145	.452
Communications	1.4	.299	.418	.255	.390
Utilities	1.5	.190	.459	.100	.395
Wholesale Trade	2.1	−.027	.483	−.077	.394
Retail Trade	8.0	−.386	.485	−.252	.405
Finance, Insurance, & Real Estate	3.9	.011	.531	.029	.417
Business Services	1.6	−.082	.599	−.082	.469
Repair Services	0.7	−.107	.425	−.136	.412
Personal Services	1.9	−.478	.491	−.216	.474
Entertainment & Recreation	0.4	.038	.616	−.038	.527
Health Services	6.2	−.130	.450	−.029	.363
Education	7.1	.123	.584	−.013	.471
Legal & Other Professional Services	2.5	−.003	.530	−.060	.469
Public Administration	5.5	.179	.491	.101	.432

[a]Sample size is 58,831, with 39,703 employed in one of the twenty-five industries.

[b]Computed relative to the aggregate log wage.

[c]Residuals from regressing log wage on age, age squared, sex, race, education, marital status, disability, SMSA, regions, and interactions of sex with age, education, race, and marital status.

establishment data, is a marginally high wage industry in the PSID. Wage rates in Construction are relatively high in the PSID, but not nearly as high as in the establishment data. This might reflect the oversampling of workers in larger firms within the establishment data.

Table 3 also reports the average of the log-wage residuals (and their standard deviations) for each industry. The residuals are derived from a common regression across the industries of log wages on individual characteristics, including age, education, sex, race, and a number of interactions. Differences in these characteristics explain some of the disparity in wage rates across industries. In absolute value, the industry wage effects average 17.9 percent using log wages and 10.7 percent using log-wage residuals. So observable characteristics reduce the magnitude of the industry effects by forty percent.

V. Empirical Results

The empirical work proceeds in three stages. First, we compare wages of industry movers to industry stayers. This reveals whether the structure of relative wages is consistent with cyclical upgrading within Roy's equilibrium model of industry selection. Second, we examine the wage changes of industry stayers. By controlling for the compositional effects of low-wage workers entering and exiting cyclical industries, this identifies the cyclical behavior of industry wage rates. Third, we compare the wage changes of industry movers to the wage changes of stayers. This tests the selection model's prediction that movers' wage changes are bounded by the wage changes of stayers in the exited and entered industries.

Mover-Stayer Wage Comparisons

For the equilibrium selection model to generate cyclical upgrading, we should observe positive selection of skilled workers into cyclical industries and negative selection into noncyclical industries and the nonmarket sector. In particular, workers entering cyclical industries during expansions should display relatively high wage rates compared to workers in the less cyclical industry from which they exit, but relatively low wages compared to workers in the cyclical industry they join; the reverse should be observed for less cyclical industries.

Table 4 displays these wage comparisons of industry movers and stayers from 1979 to 1987. To generate results by industry, we let industries sequentially take the role of industry 1, with its complement (all other industries) becoming industry 2. Comparisons are presented separately for periods when an industry's share of the population is declining and for periods when it is growing. We include observations from the nonmarket sector with imputed wages. The results are not sensitive to excluding the nonmarket sector.

Wage comparisons of industry stayers and inter-industry movers are inconsistent with our application of the equilibrium selection model to cyclical upgrading. For almost every industry, movers have relatively low wages compared both to the industry they leave and to the industry they join. Consider periods of decline. All twenty-four industries that experience some period of decline exhibit positive selection in column 1: workers who exit the declining industry were lower paid before leaving than those who remain. The difference is statistically significant for twelve industries, and positive selection is strongest for the following industries: Food and Tobacco, Paper, Printing, & Publishing, Education, and Public Administration. In column 2, for all industries except Communications, the entrants display below average wages in their new industry.

Results from expanding periods paint an even sharper picture of positive selection. In column 3, entrants have lower wages than the wages of stayers in their new industry. (Other Durables is the only exception.) The difference between the pre-move wages of leavers and those who remain (in column 4) is typically large, above thirty percent for fifteen of the twenty-six industries.[10] Overall, the wage comparisons in growing periods are 70 percent bigger than the wage comparisons in declining periods.

This asymmetry between declining and growing periods is not anticipated by the equilibrium selection model. From the perspective of the Roy model, workers appear to be

TABLE 4

Wage Comparisons of Stayers and Movers: Log Wages[a]
Panel Study of Income Dynamics, 1979–1987

Industry	Declining		Growing	
	$W_t^{11}-W_t^{12}$	$W_{t+1}^{22}-W_{t+1}^{12}$	$W_{t+1}^{11}-W_{t+1}^{21}$	$W_t^{22}-W_t^{21}$
Nonmarket	18.89 (1.63)	43.48 (1.78)	0.24 (1.68)	14.84 (1.86)
Agriculture	6.31 (8.98)	46.01 (7.43)	18.82 (11.61)	56.11 (7.35)
Mining	5.12 (9.23)	5.75 (7.06)	14.35 (9.66)	6.12 (8.07)
Construction	12.06 (4.64)	15.69 (4.06)	29.01 (4.23)	22.52 (4.17)
Metals	5.16 (4.62)	2.50 (3.89)	24.43 (10.93)	23.83 (9.00)
Machinery	10.90 (3.74)	7.20 (3.70)	26.19 (6.82)	12.89 (6.10)
Transportation Equipment	10.62 (3.93)	0.56 (4.15)	23.77 (5.68)	−0.07 (5.58)
Other Durables	6.62 (4.42)	15.38 (4.09)	−3.26 (15.22)	5.56 (15.35)
Food & Tobacco	29.44 (6.39)	30.75 (5.62)	34.61 (13.89)	26.07 (11.42)
Textiles, Apparel, & Leather	8.59 (5.24)	60.34 (4.58)	37.77 (6.69)	73.61 (7.06)
Paper, Printing, & Publishing	32.93 (9.74)	14.88 (10.13)	36.67 (10.71)	26.73 (10.17)
Chemicals, Petroleum, & Rubber	15.26 (7.01)	6.82 (6.30)	35.42 (13.42)	25.43 (11.08)
Transportation	28.46 (5.95)	19.88 (5.20)	40.97 (8.01)	22.52 (6.28)
Communications	4.04 (8.89)	−10.78 (10.13)	32.33 (10.32)	−6.64 (11.76)
Utilities	13.14 (15.89)	14.61 (14.97)	44.63 (7.09)	17.66 (6.72)
Wholesale Trade	15.43 (6.15)	11.30 (6.16)	32.75 (6.30)	20.31 (6.16)

TABLE 4–Continued

Industry	Declining		Growing	
	$W_t^{11}-W_t^{12}$	$W_{t+1}^{22}-W_{t+1}^{12}$	$W_{t+1}^{11}-W_{t+1}^{21}$	$W_t^{22}-W_t^{21}$
Retail Trade	18.57 (3.74)	52.18 (3.11)	36.71 (2.67)	62.29 (2.10)
Finance, Insurance, & Real Estate	1.47 (12.07)	0.65 (11.07)	31.19 (4.40)	26.53 (3.80)
Business Services			38.16 (5.10)	27.13 (4.01)
Repair Services	0.01 (11.21)	1.25 (7.43)	36.10 (10.36)	37.70 (8.83)
Personal Services	15.03 (11.12)	52.19 (7.78)	15.72 (5.88)	56.32 (4.59)
Entertainment & Recreation	14.76 (15.79)	6.26 (17.19)	33.58 (14.59)	13.09 (11.84)
Health Services			18.39 (3.09)	32.41 (2.79)
Education	20.83 (7.35)	15.77 (5.84)	32.11 (4.83)	27.87 (3.77)
Legal & Other Professional Services			19.18 (4.77)	12.69 (3.80)
Public Administration	24.59 (6.58)	10.01 (4.62)	44.13 (5.36)	18.25 (4.63)

[a] W_τ^{ij} is the average log wage at time τ of workers employed in industry i at time t and j at time $t+1$. Industry 1 is the designated industry; industry 2 is "all other." Standard errors are reported in parentheses.

more similar when an industry declines. From another perspective, firms appear to be more selective in hiring than in letting workers go. This is our first evidence against applying the Roy model to inter-industry mobility more generally.

Wage comparisons reported in Table 4 combine observed and unobserved components of log wages. For the question of cyclical upgrading, this is appropriate. To characterize inter-industry mobility more generally, splitting log wages into its unobserved and observed components is useful. How important is selection on unobservables relative to selection on observables? Is there positive or negative selection on the unobserved component?

Our stayer-mover comparisons of log-wage residuals in Table 5 indicate that a substantial amount of selection is on the unobserved component of log wages. (Our unobserved component of log wages is the residual from a regression of log wages on age, age^2, sex, race, education, marital status, disability, and location, as well as interactions of sex with age, education, race, and marital status.) In growing periods, entrants' wage residuals are less than those of existing workers in nearly every industry. The magnitude of these differences falls by about one-third, but positive selection remains strong for low wage, as well as high wage, industries. Periods with declining employment show little positive selection: the wage residuals of industry leavers are similar to those who stay. Thus nearly all of positive selection in declining periods is attributable to observed differences in workers.

The evidence of widespread positive selection implies considerable comparative advantage across industries, and industry labor supply schedules reflect such comparative advantage.[11] If the wages of industry entrants are substantially less than the wages of industry stayers, then labor supply to that industry is likely to be fairly inelastic. If

[10]Comparing results from Tables 3 and 4 uncovers a peculiar property: industries that have low average wages also tend to have high variances of wages. The inter-industry correlation between average log wages in Table 4 and the standard deviation of log wages in Table 2 is $-.37$. In the two-industry Roy model with log normality, the high variance industry is almost always the high wage industry. (Exceptions occur if the industries differ in size, and the larger industry has a smaller variance of wages.) If a common ordering of wage levels and variances were to carry over to the multi-industry Roy model, the negative correlation would be evidence against equilibrium selection.

TABLE 5

Wage Comparisons of Stayers and Movers: Log-Wage Residuals[a]
Panel Study of Income Dynamics, 1979–1987

Industry	Declining		Growing	
	$W_t^{11}-W_t^{12}$	$W_{t+1}^{22}-W_{t+1}^{12}$	$W_{t+1}^{11}-W_{t+1}^{21}$	$W_t^{22}-W_t^{21}$
Nonmarket	19.32	25.70	8.74	−0.98
	(1.44)	(1.50)	(1.52)	(1.58)
Agriculture	−3.10	32.79	7.66	42.87
	(7.73)	(6.67)	(10.60)	(7.81)
Mining	−6.70	5.91	0.29	−2.56
	(9.39)	(9.13)	(7.66)	(10.38)
Construction	1.90	17.17	20.48	21.82
	(4.11)	(3.60)	(3.96)	(3.77)
Metals	−0.20	7.81	−2.20	6.53
	(3.98)	(3.45)	(8.91)	(7.05)
Machinery	−1.82	7.19	14.11	10.56
	(2.96)	(3.13)	(5.87)	(5.85)
Transportation Equipment	0.84	3.34	18.40	6.04
	(3.54)	(3.64)	(5.42)	(5.37)
Other Durables	0.73	12.84	−2.26	11.75
	(3.60)	(3.31)	(9.66)	(11.38)
Food & Tobacco	14.16	19.51	34.37	26.21
	(5.83)	(5.70)	(13.04)	(8.37)
Textiles, Apparel, & Leather	6.84	32.81	26.85	36.98
	(5.23)	(3.92)	(9.04)	(6.10)
Paper, Printing, & Publishing	17.66	14.46	30.24	21.47
	(7.49)	(8.15)	(10.20)	(9.11)
Chemicals, Petroleum, & Rubber	3.16	8.23	24.97	27.37
	(5.69)	(4.71)	(9.86)	(8.89)
Transportation	18.05	22.72	27.17	20.67
	(5.64)	(5.19)	(7.86)	(6.03)
Communications	2.20	−3.41	27.02	−3.79
	(9.58)	(9.59)	(9.59)	(10.73)
Utilities	8.22	26.76	27.87	13.43
	(9.98)	(15.71)	(6.85)	(6.97)
Wholesale Trade	9.81	17.62	19.19	21.45
	(4.96)	(5.02)	(5.30)	(4.50)

TABLE 5–Continued

Industry	Declining		Growing	
	$W_t^{11}-W_t^{12}$	$W_{t+1}^{22}-W_{t+1}^{12}$	$W_{t+1}^{11}-W_{t+1}^{21}$	$W_t^{22}-W_t^{21}$
Retail Trade	6.39 (3.43)	34.23 (2.68)	22.30 (2.46)	38.36 (2.00)
Finance, Insurance, & Real Estate	−9.14 (9.74)	−0.43 (10.25)	16.36 (3.87)	14.82 (3.45)
Business Services			23.13 (4.01)	20.75 (3.09)
Repair Services	−8.02 (11.61)	6.78 (8.83)	31.17 (11.38)	41.50 (9.96)
Personal Services	−2.21 (11.35)	17.70 (6.61)	12.83 (4.97)	31.90 (4.05)
Entertainment & Recreation	−4.41 (20.38)	13.31 (21.43)	16.95 (14.14)	15.00 (11.51)
Health Services			12.45 (2.60)	18.14 (2.45)
Education	4.45 (6.11)	19.71 (4.73)	15.75 (4.25)	30.74 (3.47)
Legal & Other Professional Services			13.03 (4.15)	16.78 (3.41)
Public Administration	11.54 (5.59)	9.95 (4.28)	30.67 (4.54)	19.74 (4.17)

[a] W_τ^{ij} is the average log wage at time τ of workers employed in industry i at time t and j at time $t+1$. Industry 1 is the designated industry; industry 2 is "all other." Standard errors are reported in parentheses.

industry entrants are paid about the same as industry stayers, industry labor supply is likely to be quite elastic. Thus the relative wage comparisons can be used to indicate which industries have relatively elastic labor supply schedules.

Adopting a distributional assumption allows us to quantify the industry labor supply elasticities. We follow Roy in assuming that skills are distributed log-normally. With this assumption, the relative wage comparisons in Table 4 yield fairly large industry labor supply elasticities; the elasticities are greater than three for sixteen industries. The industry labor supply elasticities tend to be larger in cyclically sensitive industries, such as the durable manufacturing industries; indeed, the correlation between our estimated supply elasticities and the industry employment elasticities from Table 1 is .53.

Large labor supply elasticities in cyclically sensitive industries might account for the failure of relative wages in these industries to increase during expansions. (Recall from section II that cyclical industries do not exhibit more cyclical average wages.) To address this directly, we assess the compositional effects in industry average wages and search for patterns across industries in the wage changes of industry stayers.

Wage Changes of Stayers

Analyzing the wage changes of industry stayers has the advantage of purging compositional effects that contaminate fluctuations in industry average wages. From Table 4, workers moving between industries are primarily low wage workers. Therefore, as many

[11]The mover-stayer wage comparisons provide information on the selection process without imposing distributional assumptions on industry skills. With distributional assumptions, it is possible to estimate selection parameters, as well as more fundamental distributional parameters, from cross-sectional data. Following results in Heckman and Honore (1990), we estimate selection parameters from the skewness of observed industry wage distributions under the assumption that population skills (x_i's) are log normal. Reinforcing the mover-stayer wage comparisons, the industry wage distributions indicate positive selection across virtually all industries, implying considerable comparative advantage across industries. We also estimate the selection model from selection-bias corrected wage regressions (e.g., Heckman 1976; Maddala 1983), again assuming that population skills are distributed log normal. In contrast, the results show negative selection into most manufacturing industries, as well as transportation, communication, and utilities. A summary of these results is available on request.

workers move into construction and durable manufacturing during a cyclical expansion, the average skill of workers in those industries declines. This compositional effect might hide important wage movements across industries over the business cycle.

Industry wages contain important compositional effects, but the effects are not large enough to account for cyclical upgrading. Consider Construction as an example. From Table 1, a one-percent aggregate expansion in employment would typically be associated with a 2.59 percent increase in construction employment. Table 4 shows that entrants to Construction have wages averaging twenty-nine percent less than experienced construction workers. If the expansion in employment occurs through entry, this entry reduces the average wage in construction by about 0.75 percent, which is sizable. However, Table 4 shows that new entrants to the aggregate work force reduce the average wage for the economy by 0.43 percent, which is also sizable. Therefore, the compositional bias on *relative* wages in Construction is only 0.32 percent. Since the cyclical sensitivity of Construction's relative wage is estimated to be −0.49 in Table 1, correcting for the compositional bias does not reveal a procyclical relative wage for construction. Calculations for the other cyclical industries reveal even weaker compositional biases.

We can directly control for compositional effects by examining the wage changes of industry stayers. Wage changes of industry stayers identify the growth rate of each industry's wage rate ($\gamma_{it} \equiv \log \omega^*_{i,t+1} - \log \omega^*_{it}$). So fluctuations in stayers' wage changes can be used to estimate the cyclical sensitivity of industry wage rates (purged of compositional effects) and how this cyclical sensitivity varies across industries.

For each of the twenty-five industries, we calculate the average annual growth rates of wages of the industry's stayers. For each industry, this yields sixteen time-series observations corresponding to periods 1971–1972 to 1986–1987. Pooling the time series across the twenty-five industries produces a sample with nearly 400 observations. On this sample, we regress the average wage change of industry stayers on aggregate employment growth, interacted with the cyclical sensitivity of industry employment.

We do not detect clear movements in industry wage rates over the business cycle. In Table 6, we report our weighted least squares estimates of the cyclical sensitivities of industry wage rates. Scanning the results across the four empirical specifications reveals one prominent feature: statistical insignificance. Since the equilibrium model of selection requires movements in relative wages, the evidence does not support the model.

Although imprecise, the point estimates are substantial. In regression (1), we estimate that true industry wages are procyclical, with a one percent increase in aggregate employment is associated with a 0.22 percent increase in the wages of stayers. This is nearly triple the size of the aggregate wage elasticity we report using average wages in section II, above. Even the interactions with industry employment elasticities are substantial. Based on the negative interaction reported in regression (2), industries with more cyclical employment tend to have less cyclically sensitive wage rates: the implied industry wage elasticities range from 0.03 for Construction and Metals to 0.38 for Health Services.[12]

To the extent we believe the point estimates, this evidence is consistent with our evidence on relative wage comparisons. Industry labor supply functions appear to be more elastic in cyclically sensitive industries, so industry wage rates fluctuate less in industries with large fluctuations in employment. But again, the estimates are so imprecise that the evidence provides little support for the equilibrium selection model.

Wage Changes of Movers

In the absence of compensating wage differentials, the equilibrium selection model implies that the wage change of an inter-industry mover is bounded by the wage change of stayers in the mover's source industry and the wage change of stayers in the mover's target industry. We search for meaningful violations of this proposition by averaging wage changes across movers. For instance, if an industry's employment is growing, is the *average* wage

[12]The results in regressions (3) and (4), which include industry employment growth variables, are similar. In addition, regressions (3) and (4) provide some evidence that industry wages are less responsive if employment growth is industry specific.

TABLE 6

Wage Changes of Industry Stayers[a]
Panel Study of Income Dynamics, 1971–1987, Household Heads

Variable[b]	(1)	(2)	(3)	(4)
Intercept	3.52 (0.44)	3.51 (0.44)	4.05 (0.31)	3.46 (0.50)
$\Delta \log E_t$	0.22 (0.15)	0.24 (0.15)	0.20 (0.15)	0.29 (0.17)
$\Delta \log E_t \times \beta_i^e$		−0.13 (0.11)		−0.17 (0.11)
$\Delta \log(E_{it}/E_t)$			0.09 (0.09)	0.17 (0.10)
$\Delta \log(E_{it}/E_t) \times \beta_i^e$				−0.09 (0.11)
R^2	.006	.009	.009	.016
Root MSE	43.87	43.84	43.86	43.81

[a]Weighted least squares regressions using industry level data. The dependent variable is ΔW_t^{ii}, the average change in log wages of workers who stay in industry i from t to $t+1$. The weights are the number of stayers used to compute the industry-year average. With 20,637 underlying observations, the number of stayers per industry-year averages 52. With 16 time-differenced observations for each industry, and 3 missing industry-year cells, the sample size is 397. Standard errors are reported in parentheses.

[b]$\Delta \log E_t$ is the growth rate of aggregate employment; $\Delta \log(E_{it}/E_t)$ is the growth rate of industry i's employment relative to aggregate employment; and β_i^e is industry i's employment elasticity from Table 1.

growth of its entrants less than the *average* wage growth of stayers in that target industry and greater than the (weighted) *average* wage growth of stayers in all the source industries? And a similar comparison of averages applies to leavers from declining industries. Estimation amounts to computing 150 weighted averages—one for each entry in Table 7—of a single wage growth variable.[13] For this analysis, we use the the sample of household heads from 1971 to 1987.[14]

Our point estimates reported in Table 7 reveal widespread violations of the proposition. Of the forty-three possible comparisons, only three satisfy the restriction: Food & Tobacco in declining periods, and Metals and Legal & Other Professional Services in growing periods. But the wage growth estimates are not precise, especially for leavers and entrants. Indeed, statistically significant violations occur in only eight of the forty-three cases. (Retail Trade, both when declining and growing, is an example.) Given the substantial dispersion of wage changes in panel data (McLaughlin forthcoming), our sample contains too few observations on inter-industry movers for complete comparisons by industry.

Averaging the results across industries illuminates the underlying patterns. These cross-industry averages are reported in the last row of Table 7. For each of the three groups (i.e., source stayers, movers, and target stayers), wage growth is higher when the listed industry is growing. These averages also reveal a weak tendency for wage growth to be higher in target industries than in source industries. But the strongest pattern from Table 7 is that the wage growth of leavers from declining industries is too low: leavers from a declining industry tend to do worse than their co-workers who remain in the declining industry.

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[13]Formulas for the weighted average estimators are available in an appendix. The estimators for leavers and entrants reduce to computing simple averages by industry on the samples of leavers and entrants. Computing the wage growths of stayers in declining source industries and growing target industries reduces to using the sample of stayers in the listed industry, and weights their wage growths by the temporal distribution of entrants and stayers. For stayers in declining target industries and growing source industries, the estimators use the samples of stayers in all "other" industries, with weights based on year-specific mover proportions and numbers of stayers.

[14]As noted above, the quality of the spouses' turnover variables is poorer prior to 1979. Results for a sample for 1979 to 1987 that includes spouses are qualitatively similar.

TABLE 7

Wage Changes of Industry Stayers and Inter-Industry Movers
Panel Study of Income Dynamics, 1971–1987, Household Heads[a]

Industry[b]	Declining			Growing		
	Source Stayers	Leavers	Target Stayers	Source Stayers	Entrants	Target Stayers
Agriculture	1.02 (2.20)	17.39 (4.80)	4.04 (0.49)	1.61 (1.05)		13.30 (4.17)
Mining	5.53 (3.43)	4.51 (7.36)	4.05 (0.97)	1.74 (0.60)	21.56 (9.84)	2.27 (2.10)
Construction	2.68 (1.03)	−9.17 (5.50)	3.89 (0.41)	4.72 (0.39)	9.01 (4.08)	3.09 (0.82)
Metals	2.41 (0.65)	−1.02 (3.18)	4.46 (0.35)	2.37 (0.50)	3.06 (3.67)	3.28 (1.05)
Machinery	2.45 (0.59)	−5.37 (3.07)	4.62 (0.44)	3.54 (0.32)	6.38 (2.29)	4.46 (0.69)
Transportation Equipment	3.37 (0.59)	−3.77 (4.22)	3.90 (0.44)	3.36 (0.42)	1.50 (5.70)	3.30 (0.63)
Other Durables	1.84 (0.80)	−1.39 (3.57)	2.81 (0.33)	2.84 (0.45)	7.97 (3.68)	2.82 (1.10)
Food & Tobacco	2.46 (0.93)	3.53 (5.45)	3.60 (0.56)			
Textiles, Apparel & Leather	2.86 (1.07)	11.30 (4.42)	2.20 (0.39)	5.91 (1.38)		1.51 (3.56)
Paper, Printing, & Publishing	4.39 (1.21)	1.03 (6.09)	2.62 (0.52)	2.29 (1.13)		2.80 (1.36)
Chemicals, Petroleum, & Rubber	4.45 (0.82)	3.37 (5.74)	5.10 (0.47)	2.02 (0.81)	6.86 (7.06)	1.23 (1.20)
Transportation	2.74 (0.60)	−6.71 (5.94)	2.79 (0.34)	7.11 (1.07)	7.90 (8.95)	2.06 (2.00)
Communications	7.57 (1.39)	10.70 (7.34)	6.27 (0.89)	2.56 (0.60)	−11.58 (10.71)	5.71 (1.70)
Utilities	4.03 (1.38)	−7.27 (11.65)	7.86 (0.79)	2.84 (0.69)	−0.68 (10.08)	3.25 (1.55)
Wholesale Trade	7.28 (2.42)	8.12 (5.39)	6.26 (0.61)	2.88 (0.34)	−0.61 (3.68)	0.62 (1.36)

TABLE 7–Continued

Industry[b]	Declining Source Stayers	Declining Leavers	Declining Target Stayers	Growing Source Stayers	Growing Entrants	Growing Target Stayers
Retail Trade	0.33	17.24	1.71	4.57	−11.71	4.23
	(1.61)	(5.67)	(0.60)	(0.34)	(3.23)	(0.66)
Finance, Insurance, & Real Estate	1.70	−14.81	4.42	4.62	1.47	6.21
	(2.32)	(13.56)	(0.85)	(0.43)	(3.94)	(1.20)
Business Services				4.59	−5.18	8.70
				(0.34)	(4.12)	(1.91)
Repair Services	0.57		3.84	3.81	0.90	6.94
	(2.98)		(1.02)	(0.42)	(4.27)	(2.47)
Personal Services	1.39	12.82	2.89	5.82	0.60	4.12
	(3.83)	(8.76)	(0.56)	(0.69)	(8.81)	(2.30)
Entertainment & Recreation			2.88	4.42	28.08	12.30
			(1.02)	(1.01)	(9.59)	(4.54)
Health Services	5.22	6.00	5.76	3.71	1.46	2.68
	(1.16)	(4.96)	(0.56)	(0.53)	(3.81)	(0.88)
Education	3.80	−3.86	4.62	4.27	6.01	3.37
	(1.15)	(9.45)	(0.68)	(0.53)	(4.86)	(0.97)
Legal & Other Professional Services	9.09	0.80	0.07	6.47	6.66	10.80
	(4.63)	(5.65)	(0.67)	(0.45)	(3.69)	(1.81)
Public Administration	4.83	5.70	4.38	5.84	12.94	5.34
	(0.91)	(4.25)	(0.40)	(0.56)	(4.68)	(0.80)
Average Across Industries[c]	3.70	2.23	4.01	4.00	4.41	4.61

[a]There are 18,183 observations on the wage changes of stayers and 2,126 observations on the wage changes of movers. Industry averages based on fewer than 10 underlying observations are suppressed. Standard errors are reported in parentheses.

[b]The listed industry is the source industry in years when its employment is declining and the target industry in years when its employment is growing relative to total employment.

[c]Cross-industry averages are computed over the 22 declining industries and 21 growing industries with complete entries.

Our evidence on the wage changes of inter-industry movers provides little support for the equilibrium selection model. In addition, the estimates in Table 7 contain patterns across industries that are consistent with queuing. Not only is the average wage growth of leavers too low, but the wage cuts of leavers are largest in high wage industries. Indeed, the cross-industry correlation between leavers wage growth and the industry relative wage (from Table 1) is $-.53$. A similar pattern emerges for industry entrants in growing periods. Although the average wage growth of entrants is less than the average wage growth of stayers in target industries, this tends not to hold in high wage industries. The cross-industry correlation of entrants wage growth with the industry relative wage is .37. Furthermore, industries with low wage-growth leavers tend to be industries with high wage-growth entrants. The cross-industry correlation between the wage growths of leavers in declining periods and entrants in growing periods is $-.37$. These patterns are consistent with leavers being dismissed from, and entrants gaining access to high wage industries.

A complementary regression approach reinforces these inferences. We regress each mover's wage change on the average wage change of stayers in the mover's new industry, the average wage change of stayers in the mover's source industry, and a set of differenced union and industry dummy variables. Recall that the equilibrium selection model calls for positive coefficients on the industry wage change variables, and these coefficients must sum to less than one. Regression (1) of Table 8 reports that the wage change of an inter-industry mover is positively related to the wage changes of stayers in his source industry and unrelated to the wage changes of stayers in his target industry. As predicted, the coefficients sum to less than one. However, the absence of relationship between the wage changes of movers and the wage changes of target industry stayers is not predicted by the equilibrium selection model.

Also inconsistent with equilibrium selection, Table 8 presents evidence of significant industry wage effects. Controlling for changes in union status, we detect wage gains to entering and wage losses to exiting high wage industries. The employment-weighted correlation of the industry wage effects from regression (3) with the industry mean log-wage

TABLE 8

Wage Changes of Inter-Industry Movers[a]
Panel Study of Income Dynamics, 1971–1987, Household Heads

Variable	(1)	(2)	(3)
Intercept	2.81 (0.99)	2.47 (3.04)	4.09 (2.92)
ΔW^{jj}	–0.03 (0.16)	0.02 (0.17)	
ΔW^{ii}	0.25 (0.16)	0.25 (0.17)	
ΔUnion		17.25 (2.07)	17.27 (2.07)
ΔIndustry[b]		[5.36]	[5.38]
Agriculture		–8.04 (4.26)	–7.58 (4.24)
Mining		12.20 (5.08)	12.14 (5.08)
Construction		11.73 (1.91)	11.85 (1.90)
Metals		7.11 (2.55)	7.34 (2.54)
Machinery		4.55 (2.07)	4.64 (2.07)
Transportation Equipment		2.69 (2.48)	2.84 (2.47)
Other Durables		2.92 (2.48)	3.16 (2.47)
Food & Tobacco		3.12 (4.04)	3.12 (4.04)
Textiles, Apparel, & Leather		–3.64 (4.32)	–3.32 (4.32)
Paper, Printing, & Publishing		2.55 (3.88)	2.50 (3.88)
Chemicals, Petroleum, & Rubber		5.78 (3.23)	5.78 (3.23)

TABLE 8–Continued

Variable	(1)	(2)	(3)
Transportation		3.72 (2.49)	3.75 (2.48)
Communications		–9.03 (5.13)	–9.53 (5.12)
Utilities		2.18 (4.03)	2.26 (4.03)
Wholesale Trade		–2.91 (2.59)	–2.75 (2.57)
Retail Trade		–12.03 (1.67)	–11.91 (1.67)
Finance, Insurance, & Real Estate		–0.29 (2.83)	–0.76 (2.80)
Business Services		–7.39 (2.66)	–7.77 (2.61)
Repair Services		–4.18 (3.73)	–4.36 (3.73)
Personal Services		–10.31 (4.14)	–10.21 (4.13)
Entertainment & Recreation		5.24 (6.43)	4.86 (6.38)
Health Services		0.34 (2.68)	0.37 (2.68)
Education		3.08 (2.60)	3.02 (2.60)
Legal & Other Professional Services		2.42 (2.65)	2.17 (2.58)
Public Administration		2.05 (2.16)	2.02 (2.16)
Sample Size	2,167	1,947	1,947
R^2	.002	.105	.103
Root MSE	36.49	35.51	35.52

[a]Standard errors are reported in parentheses.

[b]Employment-weighted averages of the industry effects are restricted to equal zero. F statistics for the tests of zero industry effects are reported in brackets.

residuals from Table 3 is .73. So industry wage effects survive differencing.

Although the estimated industry wage effects are significant, they are less than half the magnitude of the mean log-wage residual's reported in Table 3. A regression of changes in movers' log-wages on differenced industry log-wage residuals, as well as a dummy variable for change in union status, yields an estimated slope of 0.36 (0.04); thus differencing drops the industry wage effects by nearly two-thirds. (In unreported results, we find industry wage effects are twice as large for twenty-to-thirty years olds as for older age groups.) Alternatively, the employment-weighted average magnitude of the industry wage effects from either regression (2) or (3) is 4.9, which compares to 10.7 for the industry log-wage residuals from Table 3. Consequently, a substantial fraction of inter-industry wage differences appears to be attributable to unmeasured differences in worker quality across industries, a result that contrasts with Krueger and Summers' (1988) findings.[15]

These wage gains and losses could reflect compensating differentials for various aspects of industrial employment; alternatively, they could reflect queues for employment in high wage industries. As we discussed in section III, the two hypotheses can be disentangled by examining the predictive power of past wages. Recall that in our efficiency wage model pay in the industries with queues does not reflect individual skills. Thus, if an individual moves into or out from an industry with queues, his wage at time t would poorly predict his wage in the new industry at time $t+1$. Even with jumps in pay derived from compensating differentials, equilibrium selection would not predict this.

Lagged wages are less powerful predictors of wages in the new industry for inter-industry movers entering or moving among high-wage cyclical industries. In Table 9, we

[15] We also explore whether the wages of movers are more responsive to market fluctuations than the wages of stayers. We include three additional variables in the movers' wage change regression: the growth rate of aggregate employment, and the growth rates of industry employment shares for the entered industry and the departed industry. If more senior, less-transient workers have wages that are smoothed, then we would expect positive coefficients for the employment growth rates. We find no evidence that movers' wage rates are more responsive to market conditions. The coefficients on all three variables are statistically insignificant.

report estimates of the predictive power of past wages on a sample of 1,947 inter-industry movers. With controls for union status and industry before and after the move, regression (1) reports sizable persistence in wages even for movers: the coefficient on lagged wages is 0.67. In regression (2), separate lagged wage effects are estimated for four sectoral mobility groups: movers between low wage industries, movers from high wage to low wage industries, movers from low wage to high wage industries, and movers between high wage industries. As predicted by queuing, past wages have less predictive power for workers entering a high wage industry, including those moving from one high wage industry to another. However, the wages of workers moving from a high wage industry to a low wage industry are well predicted by past wages, a result that is not anticipated by queuing. But this "anomaly" can be accommodated by admitting self-selection out of the high wage sector.

The final test distinguishes between career dynamics and efficiency wages. As we note above, industry wage effects are twice as large for twenty-to-thirty years olds as for older age groups. This is consistent with both career dynamics and age-vary efficiency wages. However, to support the career concerns of young workers, the industry wage effects should be negatively correlated with (a) industry stayers' wage growth, and (b) retention rates across industries. But for young workers, we find no relationship between industry wage effects and stayers' wage growth and a strong positive relationship between industry wage effects and retention rates. (The two correlation coefficients are .02 and .33.) So the evidence supports a selection model with efficiency wages for young workers.

VI. Summary and Conclusions

Our point of departure is cyclical upgrading, a set of industry employment, hours, and wage regularities. We empirically confirm that: industries with high wages tend to exhibit the strongest employment fluctuations; across industries, fluctuations in workweeks mimic employment fluctuations; relative to the aggregate wage, industry wages move counter-cyclically; and industries with the strongest employment fluctuations do not have more

TABLE 9

Predictive Power of Past Wages
Panel Study of Income Dynamics, 1971–1987, Household Heads[a]

Regressor	(1)	(2)
Intercept	2.27 (0.13)	1.95 (0.17)
$\log w_{t-1}$	0.67 (0.02)	
$\log w_{t-1}$ × *Sectoral Group*[b]:		
—Stays in Low-Wage Sector		0.72 (0.02)
—Enters Low-Wage Sector		0.73 (0.03)
—Enters High-Wage Sector		0.57 (0.03)
—Stays in High-Wage Sector		0.59 (0.04)
Union_t	15.61 (2.18)	15.69 (2.17)
Union_{t-1}	–11.29 (2.27)	–11.43 (2.26)
Industry_t	yes [4.66]	yes [4.52]
Industry_{t-1}	yes [2.26]	yes [1.95]
R^2	.53	.54
Root MSE	32.57	32.43

[a]The dependent variable is $\log w_t$. The sample contains 1,947 observations on inter-industry movers. Standard errors are reported in parentheses; F statistics in brackets.

[b]The high wage sector contains Mining, Construction, Metals, Machinery, Transportation Equipment, Chemicals, Petroleum, & Rubber, and Transportation. The F statistic for the null hypothesis of equal effects for the four groups is 6.45; the F statistic corresponding to the restrictions that the first two effects are equal *and* the second two effects are equal is 0.18.

procyclical wages.

To capture cyclical upgrading, we apply Roy's (1951) model of equilibrium selection to industry fluctuations. We show that a reasonable specification of the model captures the empirical patterns of cyclical upgrading. Consequently, cyclical upgrading is consistent with market clearing.

We also investigate whether this specification is consistent with inter-industry mobility patterns in panel data. The inter-industry mobility patterns are derived from comparing (a) the wages of inter-industry movers with their co-workers before and after moving, (b) the wage changes of industry stayers, and (c) the wage changes of inter-industry movers.

From two simple wage comparisons for each industry, we estimate that almost every industry is characterized by *positive selection*. That is, each industry employs workers who are above average at work in that industry. Inter-industry mobility patterns reveal widespread positive selection, but to account for cyclical upgrading the selection model requires a mix of positive and negative selection industries. Consequently, the equilibrium selection model is consistent with either cyclical upgrading or inter-industry mobility patterns, but not both.

The industry wage comparisons also contain evidence of compositional effects on wages and industry differences in labor supply elasticities. We detect important compositional effects on wages and wage movements, but the effects are not sizable enough to align employment and wage fluctuations across industries. Our industry wage comparisons also indicate that industry labor supply elasticities are more elastic in the high-wage cyclical industries. Consequently, if equilibrium selection characterizes inter-industry mobility, then large employment swings align with small wage swings because labor supply schedules are more elastic in these industries.

Our analysis of the wage changes of industry stayers, which estimates the evolution of the unobserved industry wage rate, reinforces this conclusion. Composition-corrected industry wage rates appear to be least responsive to aggregate employment in industries with the most responsive employment fluctuations. However, our estimates of movements in industry wage rates are not precise.

The equilibrium selection model fails to explain predictable patterns of wage changes for industry movers. For instance, the wages of workers leaving low wage industries to enter higher-wage cyclical industries increase by a magnitude that is inconsistent with the basic model of self-selection. Although we find evidence of substantial differences in unobserved ability across industries, industry wage effects remain—especially for young workers.

We investigate whether failures of the equilibrium selection model can be remedied by equilibrium extensions to compensating wage differentials and career dynamics, or by a queuing extension based on efficiency wages. In terms of predicting the wages of industry entrants, previous wages are less powerful for workers entering high-wage cyclical industries. Since pay in industries with queues is not as strongly related to individual skills, these industries appear to be paying super-competitive wages. Since the industry wage effects are quite small except for workers under thirty, we conclude that the evidence supports selection-based efficiency wages for young workers.

We have presented substantial evidence against an influential and reasonable market-clearing model of the labor market. However, we have not ruled out that a richer market-clearing model might be consistent with both cyclical upgrading and inter-industry mobility patterns. Nor have we been as industrious in testing the implications of queuing models. To subject queuing models to similarly rigorous testing would be valuable.

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Appendix: Weighting Variables

Let Δw_{hijt} denote the wage growth of person h, working in industry i in period t, and in industry j in period $t+1$. The set of leavers from source industry i in period t to target industry j in $t+1$ is denoted L_{ijt}, with n^L_{ijt} denoting the number of leavers from i to j *when i is declining.* E_{ijt} is the set of entrants from source industry i in t to target industry j in $t+1$, with n^E_{ijt} denoting the number of entrants from i to j *when j is growing.* For each period, let S_{it} denote the set of stayers in source industry i, and n^S_{it} the number of source stayers. And G_i is the set of time periods t for which employment in source industry i is growing. Analogous "target" sets and numbers also apply.

For each entry in Table 7, there is a weighting variable θ_{ijt} such that

$$\Delta w^D_S(i) \equiv \sum_t \sum_h \theta^D_{it} \Delta w_{hijt}, \qquad \text{where } \theta^D_{it} \equiv \frac{n^L_{it}}{n^L_i n^S_{it}} \ \forall\ t \notin G_i \wedge h \in S_{it}$$

$$\Delta w^D_M(i) \equiv \sum_j \sum_t \sum_h \theta^D_i \Delta w_{hijt}, \quad \text{where } \theta^D_i \equiv \frac{1}{n^L_i} \ \forall\ j = i \wedge t \notin G_i \wedge h \in L_{ijt}$$

$$\Delta w^D_T(i) \equiv \sum_j \sum_t \sum_h \theta^D_{ijt} \Delta w_{hijt}, \quad \text{where } \theta^D_{ijt} \equiv \frac{n^L_{ijt}}{n^L_i n^S_{jt}} \ \forall\ j \neq i \wedge t \notin G_i \wedge h \in S_{jt}$$

$$\Delta w^G_S(j) \equiv \sum_i \sum_t \sum_h \theta^G_{ijt} \Delta w_{hijt}, \quad \text{where } \theta^G_{ijt} \equiv \frac{n^E_{ijt}}{n^E_j n^S_{it}} \ \forall\ i \neq j \wedge t \in G_j \wedge h \in S_{it}$$

$$\Delta w^G_M(j) \equiv \sum_i \sum_t \sum_h \theta^G_j \Delta w_{hijt}, \quad \text{where } \theta^G_j \equiv \frac{1}{n^E_j} \ \forall\ i \neq j \wedge t \in G_j \wedge h \in E_{ijt}$$

$$\Delta w^G_T(j) \equiv \sum_t \sum_h \theta^G_{jt} \Delta w_{hijt}, \qquad \text{where } \theta^G_{jt} \equiv \frac{n^E_{jt}}{n^E_j n^S_{jt}} \ \forall\ t \in G_j \wedge h \in S_{jt},$$

and each weighting variable equals zero for observations not satisfying its respective "for all" restriction. This implies that movers from a growing industry to a declining industry receive zero weight in each calculation.

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Inter-Industry Mobility and the Cyclical Upgrading of Labor

Proposition and Proof

Kenneth J. McLaughlin

In "Inter-Industry Mobility and the Cyclical Upgrading of Labor," Mark Bils and I advance the following proposition:

PROPOSITION: If workers sort across industries on the basis of current wages, then the wage growth of movers from industry i to industry j must be greater than the wage growth of stayers in the movers' source industry (i) and less than the wage growth of stayers in the movers' target industry (j). That is,

$$\Delta W^{ii} < \Delta W^{ij} < \Delta W^{jj}$$

One should refer to the paper for the construction of the model and the notation. Here I present the proof:

PROOF: The wage growth of stayers in the two industries identifies the evolutions of the shadow prices of labor. That is,

$$\Delta W^{ii} = \log \omega_{it} - \log \omega_{i,t-1} \equiv \gamma_{it}$$
$$\Delta W^{jj} = \log \omega_{jt} - \log \omega_{j,t-1} \equiv \gamma_{jt}$$

Therefore, we must show that $\gamma_{it} < \Delta W^{ij} < \gamma_{jt}$. Since skills are time invariant, the wage growth of an inter-industry mover would have been γ_{it} had he not moved. Revealed preference—accepting the highest wage offer at time t, so $W_{it} < W_{jt}$ for a mover—implies a higher wage growth for any mover. Thus $\gamma_{it} < \Delta W^{ij}$. If an inter-industry mover had been in industry j at time $t-1$, his wage growth would have been γ_{jt}. Revealed preference at time $t-1$ implies that $W_{i,t-1} > W_{j,t-1}$ for movers, which in turn implies that $\Delta W^{ij} < \gamma_{jt}$. □

REMARKS: First, the proposition applies to each inter-industry mover, so it must hold on average for the group. Second, the revealed preference arguments depend on the absence of compensating wage differentials and transitory variation of skills. With compensating wage differentials or transitory variation of skills, we cannot invoke the two wage comparisons exploited in the proof. Third, rather than exploiting revealed preference, one can explicitly express the wage growth of movers using self-selection to truncate the random variables. A little manipulation yields $\Delta W^{ij} = \Delta W^{ii} +$ a positive term, and $\Delta W^{ij} = \Delta W^{jj} -$ a positive term.