EFFECTS OF INDUSTRY GROWTH AND DECLINE ON GENDER AND EDUCATION WAGE GAPS IN THE 1980s

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The author uses longitudinal data to study the effects of industry growth and decline on wage changes between 1976 and 2001. He finds that over this period, workers who were initially in industries that subsequently expanded enjoyed faster wage growth than other workers. Moreover, wage growth was strongly related to employment changes in industries the individual was *likely* to move to: that is, workers' wage growth tended to be relatively fast if their skills suited them for entry into rapidly expanding industries, whether or not they actually moved between industries. The author uses the estimates to evaluate the effects of industry demand changes on within-cohort relative wages during the 1980s. He finds that changes in industrial composition can account for most of the within-cohort increase in the wages of women relative to men and about 30–50% of the increase in the relative wages of more educated groups within cohorts.

In this paper, I use longitudinal data to study the effects of industry growth and decline on wages. For several reasons, a tie between wages and industry growth and decline seems likely. Even if skills are entirely general, switching costs imply that wages may differ across industries and respond to industry-specific shocks. Skills may be industry-specific because people innately match better with the tasks in some industries than in others, or because they have made investments in industry-specific skills. Thus, individuals' portfolios of skills are valued differently in different industries, and as such, the value of their human capital depends on which industries grow or decline. Since it is difficult to purchase insurance against the decline of industries one is skilled in, individuals may be exposed to a fair amount of risk. By quantifying the effects of industry decline on wages, this paper gives a sense of how large these risks are. In the empirical work, I allow industrial composition changes to affect individual outcomes through the relative growth both of the person's initial industry and of other industries the person is likely to enter.

One well-known fact is that workers who are displaced from declining industries suffer greater wage losses than do workers displaced from stable or growing industries (Carrington 1993; Neal 1995; Weinberg 2001). However, it is also likely that work-

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A data appendix with copies of the computer programs used to generate the results presented in the paper is available from the author at Department of Economics, University College Dublin, Belfield, Dublin 4.

Industrial and Labor Relations Review, Vol. 58, No. 4 (July 2005). © by Cornell University.
0019-7939/00/5804 $01.00

ers in a declining industry who are not displaced will receive lower wages than workers employed in non-declining industries. Furthermore, workers who are not in the industry but who match well with the industry should also be affected, as their reservation wage depends on conditions in the industry. Thus, this paper gives a more general account of the consequences of industry growth and decline than could be gathered by studying displaced workers alone.

The results are also relevant to an important area of research—the determinants of recent changes in the relative wages of different groups. I use the estimates to investigate how industrial composition shifts affected relative wages during the 1980s.[1] The 1980s were a period in which there were large changes in the structure of wages, particularly increases in the return to education and a reduction in the gender wage gap.

This paper complements the existing inequality literature in three main ways. First, I use panel data to study changes in relative wages within cohorts, whereas the literature has typically focused on changes across cohorts using repeated cross-sectional data. An advantage of panel data is that one can control for unobserved individual skills, provided they are fixed over time.

Second, my approach differs conceptually from that of previous studies in that individuals within demographic groups are assumed to be heterogeneous in terms of industry-specific skills. In this framework, a group is simply a collection of individuals. The literature has used shift-share analysis that is based on the assumption of homogeneity within groups. For simplicity, consider two groups, male and female, and assume a positive demand shock to a mostly female industry and a negative demand shock to a mostly male industry. In a shift-share model, this would increase the wages of all women equally and decrease the wages of all men equally. In my framework, it would tend to increase wages of all individuals who are in the mostly female industry or marginal to it *whether they are male or female.* The overall effect on the male-female wage gap would be calculated by averaging the resultant wage changes across men and women.

Third, my approach complements the literature in that the effects of industry demand shifts on wages are estimated rather than calibrated. I make no assumptions about labor supply elasticities or elasticities of substitution.

Why Do Changes in Industrial Composition Affect Wages?

I use Roy's (1951) self-selection model to analyze the effects of industry demand shocks on wages and mobility.[2] Assume n industries indexed by $j = 1, \ldots, n$. Each industry faces a downward-sloping demand for its product and has an increasing, concave production function that relates output at time t (y_{jt}) to labor input at t (L_{jt}):

$$y_{jt} = F_{jt}(L_{jt}). \tag{1}$$

There are a large number of identical firms in each industry. Firms behave competitively in labor and product markets and take both output prices, p_{jt}, and wages, w_{jt}, as given. Hence, the wage rate equals the marginal revenue product of labor (MRPL_{jt}):

$$w_{jt} = F'_{jt}\, p_{jt}. \tag{2}$$

There are a large number of heterogeneous individuals. If employed in industry j, a worker i produces l_{ij} units of output. Skills are multi-dimensional and the value of each skill varies across industries. This may be because individuals build up indus-

[1] I examine the 1980s because changes in relative wages were much greater during this decade than during either the 1970s or the 1990s.

[2] McLaughlin and Bils (2001) used a similar Roy framework in their treatment of industry mobility over the business cycle.

try-specific human capital by working in certain industries or because an individual's skills are a better match for the tasks in some industries than in others. The wage offer (W^o_{ijt}) to an individual worker in industry j is the skill price (w_{jt}) multiplied by the units of output the worker can produce in industry j:

$$W^o_{ijt} = w_{jt} * l_{ij}. \quad (3)$$

Individuals choose an industry each period by comparing the wage offers from each industry and accepting the highest offer. In competitive equilibrium, product prices (p_{jt}) clear the product market, wage rates (w_{jt}) clear the labor market, and individuals work in the industry in which they are most productive. Because workers are heterogeneous, and the distribution of skills in the labor market is assumed to be fixed, wage rates need not equalize across industries.

Consider now the effect of a positive price shock in industry k, holding output prices in all other industries constant. An increase in the price of output in industry k (p_{kt}) raises the marginal revenue product of labor in industry k (MRPL_{kt}). Workers who are already located in industry k will see their wages rise, and so it will be optimal for them to remain in industry k. Also, some workers who are located in other industries will now find that they can earn a higher income in industry k than in their current industry. These marginal workers will move to industry k until such inflows lead to a new equilibrium with higher employment and higher wage rates in industry k.

The workers who gain the most from the price change are those who were initially in industry k. Individuals who were not in industry k but on the margin of indifference between industry k and the industry they were in also gain significantly. These marginal workers are individuals for whom $\max(W^o_{ijt-1}) > W^o_{ikt-1}$ and $\max(W^o_{ijt}) = W^o_{ikt}$, where the maximum is taken over all industries, j. Other individuals benefit from spillover effects: these are people who are located in industries from which many people depart to go work in industry k. The departure of these individuals from their original industries will increase the MRPL and wage rate in those industries to some extent. However, this spillover effect is likely to be of second-order importance. The workers who benefit least are those who are not marginal to industry k or to the industries that contain a lot of workers who are marginal to industry k. Their wage rates are unlikely to change much.

To summarize, the main testable implications of the Roy model for wage changes over a ten-year period are (a) workers who started the decade in industries that subsequently expanded have greater wage growth than other workers, and (b) conditional on the employment change in the initial industry, workers who match well with an industry that subsequently grows have greater wage growth than other workers. In terms of the model, these are the marginal workers who are likely to move to the industry if it grows.

Changes in Industrial Composition

For the purposes of this study, all workers are assigned to one of 26 industry groupings. In Table 1, I list these 26 groupings along with the 1980–90 and 1990–2000 changes in log employment for each. As can be seen, the growth rate of industry employment differed greatly across industries, with 1980–90 growth rates varying between 70% in business services and –37% in mining. The industry employment data I use are provided by the Bureau of Labor Statistics (BLS).

There are many possible shocks to industry employment, and many are not observable (international trade data are available only for the manufacturing sector during this period). Like most of the literature on changes in relative wages, this study uses employment growth rates as a proxy for industry-specific labor demand shocks.[3]

[3]The results are substantively unchanged when industry employment changes are purged of an estimate of the industry employment change resulting from the shifting demographic composition of the labor force.

Table 1. Employment Changes by Industry, 1980–1990 and 1990–2000.

Industry		*1980–1990* ΔE	*1990–2000* ΔE	Industry		*1980–1990* ΔE	*1990–2000* ΔE
1	Mining and Extraction	–0.37	–0.27	14	Communication	–0.04	0.24
2	Metal Industries	–0.23	0.03	15	Other Public Utilities	0.14	–0.11
3	Machinery, including Electrical	–0.13	0.02	16	Retail Trade	0.27	0.17
4	Motor Vehicles and Other Transport	0.06	–0.07	17	Wholesale Trade	0.15	0.12
5	Other Durables	–0.02	0.01	18	Finance, Insurance, and Real Estate	0.26	0.12
6	Food and Kindred Products	–0.03	0.02	19	Repair Services	0.40	0.22
7	Tobacco Manufacturing	–0.23	–0.41	20	Business Services	0.70	0.65
8	Textiles	–0.34	–0.36	21	Personal Services	0.30	0.12
9	Paper and Allied Products	0.02	–0.06	22	Other Services	0.41	0.34
10	Chemicals, Petroleum, Rubber, and Plastic Products	0.03	0.02	23	Printing, Publishing, and Allied Services	0.23	–0.01
11	Other Manufacturing	–0.06	–0.03	24	Medical and Health Services	0.39	0.26
12	Construction	0.16	0.26	25	Education	0.38	0.34
13	Transportation	0.17	0.25	26	Government	0.12	0.12

Note: The employment changes are differences in logs.
Source: Bureau of Labor Statistics.

Evidence from the existing literature strongly suggests that changes in industry employment are largely determined by shocks to labor demand. Weinberg (2001) demonstrated a strong negative correlation between 10-year changes in aggregate industry hours and changes in the industry unemployment rate. This is consistent with changes in industry hours being driven by changes in labor demand rather than shifts in the supply of labor to individual industries. Also, if industry employment growth is driven by supply shocks, then workers displaced from growing industries should have low post-displacement wages. On the contrary, consistent with the demand-side story, post-displacement wages are higher for workers displaced from growing industries (Carrington 1993; Weinberg 2001).

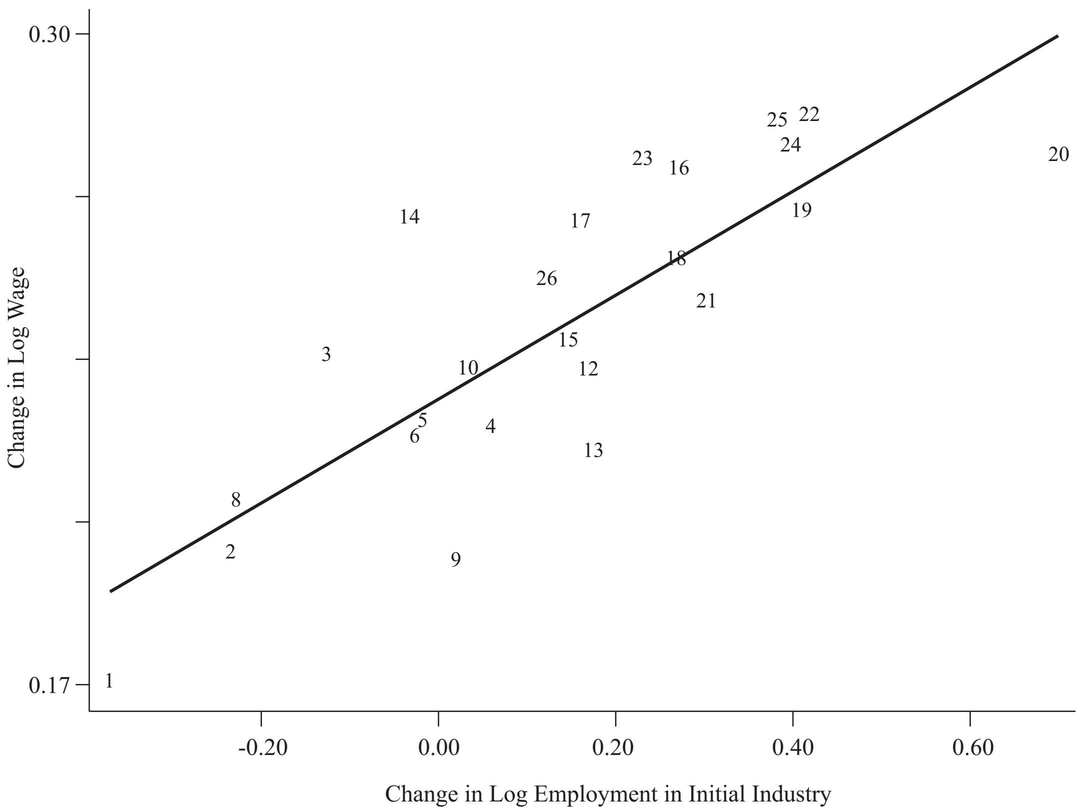
This evidence can be augmented by looking more closely at the determinants of employment changes in individual industries. Figure 1 plots the real wage changes of individuals between 1980 and 1990 against the change in log employment of the industry in which they worked in 1980 (industries are labeled by their number in Table 1; two industries are not included in the figure because they contain fewer than 5 observations). The strong positive relationship is immediately apparent. Below, I discuss the employment determinants in a few of the industries that have particularly high or low employment changes in this period:

Mining (industry 1). About half of all mining jobs are in oil and gas extraction. Because employment in mining is thus closely tied to the price of oil, it is not surprising that employment increased in the 1970s and declined during the 1980s, when oil prices rose and fell, respectively. Employment in coal mining fell during the 1980s largely due to new labor-saving technology.

Metal industries (industry 2). Metal industries, such as the steel industry, lost many jobs in the 1980s due to a mix of improved technology and increased competition from abroad.

Textiles (industry 8). Plunkert (1990) wrote, "Throughout the 1980s, [textiles and apparel] faced increasingly intense competition from imported goods, particularly goods from low-wage countries in the Far East." In response to growing imports, the textile industry invested heavily in labor-

Figure 1. The Relationship between Change in Log Industry Employment and the Average Change in Log Wages of Individuals Initially in the Industry. (Ten-Year Differences: 1980-1990)



saving capital equipment. Taken together, both these factors led to large employment falls during the decade.

Finance, Insurance, and Real Estate (industry 18). Deregulation of banking in 1980 reduced barriers to entry and was followed by rapid growth in the financial sector. Insurance agents and real estate agents also grew in number over this period.

Business Services (industry 20). This industry grew rapidly as companies responded to competitive pressures by outsourcing more of their labor requirements to contract and temporary help firms.

Medical and Health Services (industry 24). The health industry grew rapidly during the 1980s due to the aging of the population, technological advances in treatments, and greater paperwork requirements imposed by government and insurance companies. Also, health insurance coverage increased over the decade and the proportion of costs paid directly by patients declined from 27% to 19% (Hiles 1992). This implied a positive shift in demand for health services.

Thus, for many industries, there are clear shocks to labor demand that resulted in changes in industry employment.

Econometric Methodology

The analysis uses long difference estimation: I regress individual log wage changes between t and $t + 10$ on industry employment change variables and on worker characteristics. The model suggests that the largest benefits of a positive demand shock to an industry accrue to those who were initially in the industry. Therefore, for a worker in industry j at time t, I allow changes in wages between t and $t + 10$ to depend on changes in log employment in industry j between t and $t + 10$. I call this variable CH_OWN.[4] Note that the specification conditions on the employment change in the initial industry *irrespective of whether the worker is still in that industry at time t + 10.*

However, the model points out that workers' wages will also be affected by the performance of industries the workers are close to the margin of entering. Therefore, I weight the employment change in each industry k (not equal to j) by the probability that a worker of type i in industry j moves to that industry. This weighted sum of employment changes across industries for each individual of type i in industry j is called CH_OTH. In practice, I create this variable using four types of workers—men and women with and without college degrees.[5]

To create CH_OTH, I require a large sample of industry changers. I use the Annual Demographic Files of the CPS for the years 1976 to 2001. In the CPS, I treat an individual as having changed industries if the industry of the longest-held job in the previous year is different from the industry of the current job reported in March. (To do so, I aggregate the 3-digit industry codes in the CPS into the same 26 industry groups defined in the PSID.) Out of the full CPS sample of 1,705,770 employees, I have 175,088 industry changers. This sample is used to create the CH_OTH variable by sex, college degree, and industry. For each industry, I calculate the proportion of type i industry changers who move to each other possible industry. Then I weight the change in log employment in each industry by the proportion of workers who move to that industry, given their current industry and type. The CH_OTH variable for each person-year is the sum of the weighted log employment changes,

$$\text{(4)} \qquad \text{CH\_OTH}_{ijt} = \sum_{k \neq j} \pi_{ijt} \Delta \log(E_{kt}),$$

where π_{ijt} is the proportion of industry changers of type i who were in industry j and move to industry k.[6] I then merge this variable back into the PSID by sex, college degree, industry, and year.[7]

From the Roy model, we would expect the signs of the coefficients on CH_OWN and CH_OTH to be positive. The magnitude of CH_OWN relative to CH_OTH is difficult to predict. If people only match well with two industries (their initial industry and one other), then CH_OTH would be employment growth in the other industry they

[4]Because changes in employment over 10 years include both transitory and persistent components, I have tried fitting a quadratic trend to industry employment over the sample period. I find that the trend component of industry employment changes has an effect on wage changes that is very similar to the total effect of industry employment changes.

[5]Further disaggregation by race, though desirable, is not feasible, because many of the cells of nonwhites would have too few observations.

[6]There will be some measurement error if either the origin industry or destination industry is misclassified. Since I am calculating means, much of this error will be averaged out.

[7]A different way of thinking about how a worker may be affected by employment changes of industries other than his own is in terms of spillover effects. If an industry declines, then workers from that industry will move to other industries and hence affect the wages of workers in those industries. In particular, workers of a certain type are likely to be adversely affected by an inflow of similar workers into their industry. I have quantified this effect for a person of type i in industry j by calculating the weighted employment changes across industries, with the weight being the probability that someone of type i who leaves that industry enters industry j. This variable was created using the same CPS sample and also merged to the PSID by race, college degree, industry, and year. The coefficients on this variable were very similar to those on CH_OTH. This is unsurprising, as these two variables are very highly correlated. Essentially, it appears that although the two variables differ in the theoretical motivation for their use, they are measuring the same thing.

match well with. In that case we would expect the coefficient on CH_OWN to exceed the coefficient on CH_OTH. However, if individuals match well with 10 other industries (with an equal probability of moving to each), then CH_OWN would equal CH_OTH if the initial industry grew by one-tenth as much as one of the 10 industries represented in CH_OTH. *A priori,* we cannot tell in the Roy model whether an individual would gain more from a positive demand shock to his initial industry or from a demand shock that is 10 times the magnitude in another industry that he matches well with. Thus, it is consistent with the Roy model for the coefficient on CH_OTH to be larger or smaller than the coefficient on CH_OWN.[8]

Data

The longitudinal data used throughout this paper come from the 1976–2001 survey years of the Panel Study of Income Dynamics (PSID). The 1994–2001 files are early release files, and there was no interview in 1998 or 2000. I include individuals aged between 18 and 55 in the initial period. There are two wage measures in the PSID: the reported hourly wage rate at the interview date, and average hourly earnings in the previous calendar year. Because each wage measure has advantages and disadvantages, I report estimates for both measures.[9] Wages are deflated by the GDP consumption deflator.[10]

I delete observations with missing values for the race and education variables, and a small number of cases where fewer than 200 observations were used in the CPS to construct CH_OTH. I also delete cases in which the person is employed in agriculture or fisheries. For most of the analysis the sample is further restricted to working persons who are also in the sample and working exactly 10 years later. Thus, the initial periods come from survey years 1976–91, with the 1986–2001 surveys providing observations on $t + 10$ wages. Note that the Current Wage relates to the interview date, while Average Hourly Earnings refer to the previous calendar year. To time the variables appropriately, I link Average Hourly Earnings to industry employment in the previous calendar year (where the industry is that in which the individual worked in the previous year). The experience variable refers to actual labor market experience rather than potential experience. Table 2 provides some descriptive statistics for selected variables in the Average Hourly Earnings sample and Current Wage sample.

Industry Employment Changes and Wage Changes

The estimating equation relates ten-year changes in log wages to (a) ten-year changes in log employment in the initial industry (CH_OWN) and (b) 10-year changes in log employment in industries the individual is likely to move to (CH_OTH). There are also

[8]I also tried using the employment change of the industry in which the individual worked in the previous year. When I did so, the estimates were about half the size of the coefficients on employment change in the current industry. Adding employment growth in the previous industry has little effect on the explanatory power of the regression, and so I do not use it in this paper.

[9]The average hourly earnings measure has the advantage of including income from bonuses, overtime, and commissions and being available for all individuals who worked any hours during the previous calendar year. This minimizes selection problems due to non-participation. I discuss these selection issues further below, under "Specification Checks and Extensions." An advantage of the current wage is that it is matched more cleanly to the industry, as both correspond to the job the individual is working on at the interview date. It is also likely to be measured with less error. However, the current wage is missing for individuals who are not working at the survey date.

[10]A small proportion of both Average Hourly Earnings and Current Wage observations are topcoded. I impute topcoded values for both of these measures by multiplying the topcoded value by 1.33. To reduce the influence of outliers and measurement error, I delete wage observations that are less than \$2.50 or greater than \$100 in 1997 dollars.

Table 2. Means of Selected Variables: PSID, 1976–1991.

Variable	*Obs.*	*Mean*	*Std. Dev*	*Min.*	*Max.*
		Average Hourly Earnings Sample			
Female	51,235	0.47	0.50	0.00	1.00
White	51,235	0.70	0.46	0.00	1.00
Years of Experience	51,235	13.36	7.96	0.00	41.00
Education Less Than High School	51,235	0.13	0.34	0.00	1.00
High School Graduate	51,235	0.60	0.49	0.00	1.00
College Degree	51,235	0.27	0.44	0.00	1.00
10-Year Change in Log Wage	51,235	0.17	0.56	–3.05	3.58
CH_OWN	51,235	0.19	0.19	–0.57	0.78
CH_OTH	51,235	0.23	0.06	0.07	0.37
Same Industry at t and $t + 10$	51,235	0.44	0.50	0.00	1.00
		Current Wage Sample			
Female	35,445	0.46	0.50	0.00	1.00
White	35,445	0.70	0.46	0.00	1.00
Years of Experience	35,445	13.45	7.68	0.00	41.00
Education Less Than High School	35,445	0.12	0.33	0.00	1.00
High School Graduate	35,445	0.60	0.49	0.00	1.00
College Degree	35,445	0.28	0.45	0.00	1.00
10-Year Change in Log Wage	35,445	0.17	0.42	–3.02	3.20
CH_OWN	35,445	0.18	0.19	–0.57	0.78
CH_OTH	35,445	0.22	0.06	0.07	0.37
Same Industry at t and $t + 10$	35,445	0.47	0.50	0.00	1.00

controls for worker characteristics in the initial period and year indicators.[11] The sample runs from 1976 to 1991, so the ten-year periods are from 1976–86 through 1991–2001. The standard errors are calculated by bootstrapping from individual clusters so they take account of the fact that there are repeated observations on individuals.[12]

The estimates from the pooled regressions are reported in Table 3. The coefficient on CH_OWN is 0.18 for both wage measures and is statistically significant. The coefficient on CH_OTH is 0.57 for average hourly earnings and 0.68 for the current wage, and in both cases it is statistically significant. Because the results are generally similar for both wage measures, the exposition will focus on the average hourly earnings results.

As described earlier, *a priori* the coefficient on CH_OTH could reasonably be larger or smaller than the coefficient on CH_OWN: if individuals match well with 10 other industries, the coefficients imply that what happens in one of those 10 industries is about one-third as important as what happens in their initial industry. As discussed earlier, the interpretation of the coefficient depends on the number of industries that individuals match well with. The weights used to construct CH_OTH are quite dispersed, with typically many industries having weights of greater than 0.05 and no industries having weights of greater than 0.30. Thus, the estimated coefficient on CH_OTH is consistent with the Roy model, given that individuals appear to match well with several different industries.

[11]These controls are a cubic in experience, indicator variables for female and white, three education dummy variables (high school dropout, high school diploma, college degree), and a complete set of interactions of all these variables.

[12]I also experimented with allowing for clustering in CH_OWN and CH_OTH, arising from the presence of industry-year-specific error components. This had negligible effects on the standard errors (about 10% for CH_OWN and 5% for CH_OTH).

Table 3. Effects of Changes in Industrial Composition on Wages (10-Year Differences).

	Average Hourly Earnings		*Current Wage*	
Sample	*CH_OWN*	*CH_OTH*	*CH_OWN*	*CH_OTH*
Full Sample	0.177***	0.568***	0.178***	0.683***
	(0.020)	(0.108)	(0.018)	(0.111)
By Education:				
High School Dropouts	0.031	0.829**	0.094**	0.804***
	(0.053)	(0.326)	(0.045)	(0.253)
High School Graduates	0.196***	0.593***	0.155***	0.951***
	(0.028)	(0.154)	(0.023)	(0.130)
College Degree	0.192***	0.394*	0.239***	0.246
	(0.042)	(0.227)	(0.045)	(0.212)
By Gender:				
Female	0.187***	0.468**	0.204***	0.574***
	(0.035)	(0.178)	(0.026)	(0.174)
Male	0.173***	0.548***	0.168***	0.588***
	(0.031)	(0.148)	(0.025)	(0.130)
By Race:				
Nonwhite	0.202***	0.167	0.141***	0.523***
	(0.038)	(0.194)	(0.030)	(0.153)
White	0.174***	0.764***	0.203***	0.778***
	(0.025)	(0.127)	(0.024)	(0.131)
By Age:				
Experience ≤ 10	0.218***	0.919***	0.214***	0.972***
	(0.031)	(0.154)	(0.034)	(0.175)
Experience > 10	0.138***	0.327**	0.149***	0.492***
	(0.025)	(0.151)	(0.026)	(0.128)
By Age and Gender:				
Women, Experience ≤ 10	0.249***	0.305	0.199***	0.664***
	(0.039)	(0.237)	(0.038)	(0.239)
Women, Experience > 10	0.123**	0.620**	0.209***	0.490*
	(0.046)	(0.282)	(0.040)	(0.253)
Men, Experience ≤ 10	0.201***	1.417***	0.248***	1.024***
	(0.042)	(0.241)	(0.040)	(0.198)
Men, Experience > 10	0.150***	0.060	0.120***	0.329**
	(0.031)	(0.163)	(0.029)	(0.166)
By Switcher Status:				
Industry Stayer	0.081***	0.539***	0.100***	0.463***
	(0.029)	(0.138)	(0.025)	(0.146)
Industry Mover	0.229***	0.524***	0.219***	0.800***
	(0.029)	(0.140)	(0.020)	(0.130)

Additional controls are listed in the text. There are 51,235 observations on Average Hourly Earnings and 35,445 observations on the Current Wage.

Standard errors take account of the fact that there are repeated observations on individuals (see text for details).

*Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.

An alternative way to assess the magnitude is to compare the effect of a one standard deviation change in CH_OTH to the effect of a one standard deviation change in CH_OWN. The effects are about 0.03 for both CH_OWN and CH_OTH. Thus, using this metric, the impact of CH_OTH on wage changes is similar to the impact of

CH_OWN on wage changes. Of course, measurement error in initial industry might cause the estimates to understate the effects of CH_OWN on wage changes and correspondingly overstate the effects of CH_OTH.[13] The fact that employment changes in industries other than the initial industry matter suggests that workers have skills that are valuable in more than one industry but are not purely general.

In the remainder of Table 3, the regression is estimated by demographic group. The disaggregated estimates are generally not very precisely estimated, but some patterns emerge. More educated individuals appear more influenced by what happens to their initial industry and less affected by CH_OTH. This is somewhat surprising, as one might expect more educated workers to be more mobile and thus less influenced by conditions in their initial industry. Estimates are similar by gender and not so different by race. When the regression is estimated by experience level, with the division being at 10 years of experience, young workers are found to be more sensitive to both CH_OWN and CH_OTH (both differences are statistically significant). When the young/old comparison is carried out by gender, the differences by experience are statistically significant only for men. It may be that older workers are less willing to take wage cuts, since employment losses are likely to disproportionately affect young, marginal workers. The results are consistent with the notion that young people are more mobile than older workers and are better able to take advantage of opportunities when their industry is growing. They are also likely to be the ones who lose their jobs when their industry is doing poorly. The estimates are consistent with more experienced men being somewhat protected by implicit contracts. The greater importance of CH_OTH for the young appeals to intuition and is in keeping with expectations from the Roy model: the young are more mobile and have less firm- and sector-specific human capital, and so are more likely to match well with many industries and be influenced by demand shocks to a number of different industries.

Finally, the regressions are estimated separately for individuals who are in the same industry at t and $t + 10$, and persons who have switched industry between the two periods.[14] I find that CH_OWN has larger effects on industry movers than on industry stayers; the effects of CH_OTH are similar for the two groups. The positive effects of both variables on industry stayers suggest that the effects are not simply coming through changes in industry rents (I consider rents in the next section). The strong positive effects of CH_OTH on both movers and stayers imply that workers gain from employment growth in industries they match well with even if they do not actually switch industry. This is consistent with a model in which good outside options improve bargaining power. It could also reflect a pure selection effect: individuals who remain in an industry even though their outside options are very good must do so because they have rapid wage growth in their industry. One should be cautious in interpreting these results, given the inherent selectivity involved in the decision of whether or not to switch industries. In looking at these two groups separately, we are conditioning on an endogenous variable.

In Table 4, I report estimates that are broken down by time period in order to examine whether the estimates are reason-

[13] Mellow and Sider (1983) compared CPS industry reports to employer reports and found 92.3% agreement at the 1-digit level and 84.1% agreement at the 3-digit level. Given that the employers probably also misreport industry, these are lower-bound indications of the proportion of correct replies. Given that these misreporting levels are quite low, it is unlikely that misreporting is causing sizeable biases in the estimates.

[14] Because there were no surveys in 1998 and 2000, previous year industry is unavailable in 1999 and 2001. For these two years, I treat the industry at the interview date as the previous year industry.

ably constant across time. First, separate regressions are run for each year. The first column of Table 4 lists the initial survey year used in the 10-year differences. The estimates are somewhat imprecise and vary greatly in magnitude from year to year, but there are no strong temporal patterns. In the last five rows, observations are pooled into three subperiods based on the initial interview year. There are no statistically significant differences between estimates for the three subperiods. Finally, in the bottom two rows, estimates are presented for pooled regressions using the 1980–82 survey years (1979–81 for the Current Wage) and the 1979–83 survey years (1978–82 for the Current Wage), respectively. For both wage measures, these specifications provide estimates for the 1980s (later we will examine changes in relative wages during this decade). Once again, the estimates are similar to those from the pooled regression in Table 3. In summary, while the lack of precision rules out definitive conclusions, it appears that there are no large changes in the size of the estimates over the sample period.[15]

Specification Checks and Extensions

Specification Checks for Unobserved Heterogeneity

One might worry that individuals who are initially in industries that subsequently grow are different from those in industries that subsequently decline, and that they would have had faster wage growth in any case. Because I include controls for education, experience, race, and sex, the industry employment coefficients are not capturing differential wage growth across education, experience, race, or gender groups. However, there are large unexplained wage differences across industries that suggest the possibility of sizeable unobserved cross-industry differences between workers. I have carried out three simple specification checks to examine whether this is likely to be a source of bias.

First, because rates of wage growth may differ across wage levels, I have added the average wage of the individual at t and $t+10$ as an extra explanatory variable. In the regression, the coefficient on this variable is positive and statistically significant. The addition of this control causes the coefficient on CH_OWN to rise slightly (from 0.18 to 0.20) while the coefficient on CH_OTH remains unchanged.

Second, because more skilled individuals may compose the work forces of high-wage industries, I have also added the average wage across all workers in the industry as a control variable. The addition of this control has no effect on the industry employment coefficients.

Third, workers in declining industries are more likely to be unionized than are workers in stable or expanding industries, and union status may have an independent effect on wage growth. I have tried adding a control for union status in the initial period, and I find that it has very little impact on the industry employment coefficients. Also, I have tried adding a control for the change in the industry unionization rate over the 10-year period. The coefficient on CH_OWN remains unchanged, and the coefficient on CH_OTH falls slightly to 0.43.

Therefore, I am confident that the wage growth differences across industries that are correlated with industry employment growth do not merely reflect underlying differences in the types of workers across industries.

Adding the Average Employment Change in Industries with Which the Individual Matches Poorly

The model implies that employment increases in industries to which the individual

[15]The CH_OTH measure does not take account of the fact that the proportion of industry stayers differs across industries. Therefore, I also tried interacting CH_OWN and CH_OTH with the proportion of individuals in the CPS cell who remain in the same industry from year to year. I find that the interactions have the correct sign: 0.626 (0.615) for the interaction with CH_OWN, and –4.554 (2.700) for the interaction with CH_OTH. Obviously, however, these interactions are not precisely estimated.

Table 4. Estimates by Time Period.

	Average Hourly Earnings		Current Wage	
Initial Period	CH_OWN	CH_OTH	CH_OWN	CH_OTH
1976	0.208***	–0.133	0.100**	0.119
	(0.059)	(0.374)	(0.048)	(0.272)
1977	0.141**	–0.187	0.126**	0.383
	(0.057)	(0.337)	(0.054)	(0.268)
1978	0.086	0.786**	0.181***	0.172
	(0.056)	(0.301)	(0.059)	(0.289)
1979	0.133**	0.309	0.194***	0.508**
	(0.058)	(0.303)	(0.046)	(0.233)
1980	0.236***	0.230	0.177***	0.832***
	(0.054)	(0.284)	(0.045)	(0.238)
1981	0.232***	0.650**	0.195***	0.836***
	(0.055)	(0.290)	(0.046)	(0.242)
1982	0.247***	0.053	0.251***	0.594**
	(0.054)	(0.291)	(0.045)	(0.252)
1983	0.136**	1.128***	0.294***	0.450
	(0.058)	(0.327)	(0.066)	(0.371)
1984	0.318***	0.474	0.270***	0.476*
	(0.061)	(0.328)	(0.049)	(0.259)
1985	0.165***	0.460	0.146***	0.831***
	(0.060)	(0.316)	(0.047)	(0.259)
1986	0.131**	0.770**	0.204***	0.723**
	(0.056)	(0.312)	(0.049)	(0.273)
1987	0.210***	0.537	0.185***	1.124***
	(0.065)	(0.366)	(0.054)	(0.308)
1989	0.180***	0.551	0.124**	0.518*
	(0.063)	(0.368)	(0.052)	(0.298)
1991	0.128**	0.819**	0.141***	0.739***
	(0.056)	(0.336)	(0.043)	(0.267)
1976–1980	0.156***	0.368**	0.157***	0.495***
	(0.033)	(0.181)	(0.027)	(0.158)
1981–1985	0.214***	0.551***	0.217***	0.701***
	(0.032)	(0.167)	(0.029)	(0.141)
1986–1991	0.157***	0.766***	0.162***	0.840***
	(0.032)	(0.179)	(0.028)	(0.189)
1980s (3-year period)	0.236***	0.320*	0.189***	0.724***
	(0.039)	(0.191)	(0.031)	(0.165)
1980s (5-year period)	0.196***	0.473***	0.201***	0.599***
	(0.033)	(0.171)	(0.027)	(0.151)

Notes: See notes to Table 3.

is very unlikely to move should have little effect on the individual's wage. I construct such a variable by choosing the industries to which the individual has a less than 1% chance of moving (using the same CPS data used to construct CH_OTH). The employment changes in these industries are then averaged. When this variable is added to the specification for average hourly earnings, it has a coefficient of –0.002 with a standard error of 0.088. The coefficients on CH_OWN and CH_OTH are not affected by the inclusion of this variable.

Attrition and Non-Participation

Because the analysis uses long differences, there is a concern that attrition may lead to biases in the estimated coefficients. Selection issues obviously arise given the non-randomness of the pattern of observations across which data are non-missing at $t + 10$. It is well known that a worker's probability of dropping out of the PSID is related to that person's observable characteristics and to his or her wages at t (Fitzgerald et al. 1998). Likewise, the probability of not working at $t + 10$ may depend on wages and industry affiliation at t. Therefore, this issue requires some attention.

A formal approach to the missing data problem is to model the probability that a worker will have non-missing data at $t + 10$. I allow the probability of attrition or non-participation to depend on the variables that are always observed, w_{it} and z_{it}. (The latter includes the variables in x_{it} [the set of controls used in estimating equation 4], CH_OWN, and CH_OTH.) However, I do not allow dependence on the variable that is missing for some units, $w_{i,t+10}$. Let D_i be an indicator function that takes a value of one if there are full data for an individual at $t + 10$ and zero otherwise:

$$(5) \qquad \Pr(D_i = 1 | W_{it} = w_{it}, W_{i,t+10} = w_{i,t+10}, Z_{it} = z_{it}) = g(w_{it}, z_{it}),$$

with $g(\cdot)$ unknown. The estimation of this model is carried out in two steps. In the first stage, I estimate a logit model that conditions the probability of attrition or non-participation on w_{it} and z_{it}. The predicted probabilities from the logit model are used to form weights, and these weights are used to weight the observations in the second step. The weights are equal to the inverse of the probability of being in the sample at $t + 10$.[16] When I implement this procedure I find that the weighted results for the industry employment variables are almost identical to the unweighted results. Thus, the fact that data are missing for many people at $t + 10$ does not appear to lead to large biases in the estimates of interest.[17]

The Effects of Industry Employment Changes on Competitive Wages and Rents

I did not make any distinction earlier between competitive wages and rents because rents are difficult to measure and their very existence is somewhat controversial (Krueger and Summers 1988; Murphy and Topel 1990). I consider that issue here. First, I estimate a rent for each industry as the coefficient on the industry dummy in an individual fixed effects log wage regression that includes all the control variables that are time-varying. I then subtract the estimated industry rent from the log wage of each worker within that industry to arrive at an estimate of the competitive wage for that worker in that year.

I have estimated specifications in which the dependent variable is the change in the wage between t and $t + 10$, net of industry rents. For average hourly earnings, the coefficient on CH_OWN is 0.077 (0.025) and the coefficient on CH_OTH is 0.382 (0.127). For the current wage, the coefficient on CH_OWN is 0.118 (0.020) and the coefficient on CH_OTH is 0.372 (0.126). Thus, it appears that some, but far from all, of the effects of both CH_OWN and CH_OTH can be attributed to their effects on rents received by workers.

[16]This is referred to as Missing at Random (Rubin 1976; Little and Rubin 1987).

[17]As another check for attrition bias, I estimated regressions based on five-year differences. I did so both using all available observations and using a sample restricted to observations for whom data were available at $t + 10$ as well as at $t + 5$. The coefficients on the industry employment variables are almost identical in both of these cases. In addition, I estimated the model for a group with low attrition—white men with college degrees who were no more than 40 years of age in the initial period. For this group, the coefficient on CH_OWN is 0.195 (0.072) and that on CH_OTH is 0.624 (0.343).

Industry Employment Changes and Group Wage Changes

Given the finding that changes in industry employment had large effects on wages, it is appropriate to revisit the question of how these industry shifts affected the relative wages of different groups of workers during the 1980s. Industry demand shocks may affect relative wages because the distribution of individual portfolios of industry-specific skills differs across groups. Because average hourly earnings are available for a broader sample of individuals, all analysis in this section uses this wage measure.

Consider the actual 10-year wage changes by sex-education group in Table 5. Note that these are calculated as the average 10-year change in the log wage for individuals in the relevant group (to improve precision, survey years 1980–82 have been used for the initial period). Thus, these are within-cohort changes in relative wages. Wages of women with college degrees rose by about 25% over the decade. In contrast, wages of male high school dropouts fell by 3% over this period. At a more aggregate level, the average woman experienced a wage increase of 16%, far higher than the 8% increase of the average man. Similarly, comparing by educational attainment, the average degree holder attained a 22% increase in wages. This compares to a 10% increase by high-school graduates and a 2% change for high school dropouts. Finally, one can see that the differences in wage growth by race are small, with whites having marginally higher wage growth than nonwhites.

It is worth noting that the trends in relative wages here are very similar to those reported in the CPS over a similar period. Bound and Johnson (1992) reported an increase in the college degree/high school graduate differential of about 0.14 log points and an increase in the high school diploma/high school dropout differential of about 0.07. The corresponding numbers in Table 5 are 0.12 and 0.08. Bound and Johnson showed female wages increasing by 0.08 log points relative to male wages, exactly the same as in Table 5. They did not study the black/white wage differential. Their time period was 1979 to 1988, whereas mine is 1979–81 to 1989–91. Katz and Murphy (1992) reported similar changes. The similarity of the changes in relative wages is consistent with the claim of Katz and Autor (1999) that changes in relative wages follow patterns within experience groups similar to those within cohorts. On the other hand, Blau and Kahn (1997) reported a change in the male-female wage gap in the PSID between 1979 and 1988 of about 0.15 log points. It makes sense that the change in the male-female wage gap should be smaller in my composition-constant sample, as women's education and experience were rapidly improving over this period.

As Table 5 shows, there is certainly a correlation between the relative wage changes of different groups and the industry employment change variables during the 1980s. For example, among the six sex-education groups, the ranking of 10-year changes in log wages lines up exactly with the ranking of CH_OWN. The value of CH_OTH is also generally higher for groups with faster wage growth. Whether the sample is divided by race, by sex, or by education, the rankings of the two employment change variables line up with the ranking of the wage change for the group.

In this section, I use the estimation results from earlier to quantify this relationship. Specifically, I weight the group differences in CH_OWN and CH_OTH by the regression coefficients from Table 3. For example, using Table 3's coefficients on CH_OWN (0.18) and CH_OTH (0.57), one gets $0.18*(-0.103) + 0.57*(-0.079) = -0.063$ log points predicted change in the male-female wage gap due to gender differences in industry growth rates. Given the total change in the male-female gap of 0.079 log points, this suggests that most of the change can be accounted for by the fact that women were much more likely than men to be in fast-growing industries or to move to fast-growing industries. Similarly, when one looks at the pattern by education group, changes in industry employment have a

Table 5. Wage Changes and Employment Changes by Group During the 1980s (means).

Group	*10 Year Change in Log Wage*	*CH_OWN*	*CH_OTH*	*Explained by Industry Variables*	*Experience*	*Explained by Experience*
Female, no Diploma	0.084	0.180	0.250		12.321	
Female, no Degree	0.150	0.222	0.258		10.162	
Female, Degree	0.250	0.333	0.315		11.020	
Male, no Diploma	–0.028	0.085	0.159		17.606	
Male, no Degree	0.057	0.112	0.173		13.650	
Male, Degree	0.205	0.222	0.244		15.215	
Male No Diploma/Female Degree Difference	**–0.278**	**–0.248**	**–0.156**	**–0.133**	**6.586**	**–0.072**
Male	0.084	0.137	0.190		14.698	
Female	0.163	0.240	0.269		10.625	
Male/Female Difference	**–0.079**	**–0.103**	**–0.079**	**–0.063**	**4.073**	**–0.045**
White	0.129	0.193	0.228		13.079	
Nonwhite	0.103	0.171	0.226		12.110	
White/Nonwhite Difference	**0.026**	**0.022**	**0.002**	**0.005**	**0.969**	**–0.011**
No Diploma	0.019	0.125	0.198		15.381	
No Degree	0.104	0.168	0.216		11.886	
Degree	0.223	0.268	0.273		13.479	
No Diploma/Degree Difference	**–0.204**	**–0.143**	**–0.075**	**–0.068**	**1.902**	**–0.021**
No Degree/Degree Difference	**–0.119**	**–0.100**	**–0.057**	**–0.049**	**–1.593**	**0.018**

Wage changes are calculated as the average 10-year change in the log wage for individuals in the relevant group in survey years 1980–82.

The amount explained by industry variables is calculated by weighting the group differences in CH_OWN and CH_OTH by the regression coefficients from Table 3. For example, using Table 3's coefficients on CH_OWN (0.18) and CH_OTH (0.57), one gets 0.18*(–0.103) + 0.57*(–0.079) = –0.063 log points predicted change in the male-female wage gap due to gender differences in industry growth rates.

Experience refers to the average labor market experience of individuals in the relevant group during 1980–82.

The amount explained by experience is calculated using differences in average experience levels across groups (based on a coefficient of –0.011 on experience in a regression of the change in log wages on experience plus the other demographic controls).

large impact on changes in relative wages (0.075 of the 0.204 log point increase in the gap between degree holders and high school dropouts can be explained by the industry variables). About one-half of the smaller disparity in wage growth between high school graduates and college graduates can be explained by the employment variables. On the other hand, changes in industry employment seem to have little impact on the relative wage growth of blacks and whites.

The results by sex-education group are also shown in Table 5. I have not disaggregated further by race, because of the earlier finding that changes in industry employment can explain little of the small white-nonwhite wage growth disparity. Changes in industry employment can account for a substantial amount of the performance differences between these more detailed groupings. For example, the difference in wage growth between female degree holders and male high school dropouts is about 0.28 log points—0.13 of which can be explained by the industry variables.[18]

[18]One should note that there were increases in the relative supply of highly educated workers during the 1980s. Thus, shifts in industry demand would likely explain a smaller proportion of changes in relative wages net of the effects of supply effects.

Wage changes may differ between groups because of labor market experience differences. Generally, workers with fewer years of labor market experience have faster wage growth. This issue is of particular importance when considering changes in the relative wages of men and women in this sample, because women have much less experience. In the last two columns in Table 5, I list average group experience and the amount of the change in average wages that can be explained by experience differences (based on a coefficient of –0.011 on experience in a regression of the change in wages on experience plus the other demographic controls). The main effect of experience is in explaining the male-female changes—0.045 log points in the change in the gender wage gap can be attributed to the fact that the women in that sample had lower experience at the beginning of the decade.[19]

All in all, the results suggest that changes in industry employment had a large effect on changes in relative wages during the 1980s. The relative wages literature has used changes in industry employment to proxy for product demand shifts. As discussed above (under "Changes in Industrial Composition"), changes in industry employment are probably largely determined by industry-level shifts in labor demand. However, they may not occur as a result of shifts in product demand. For example, textile employment changes were affected by both product demand shocks and technological change. Thus, one should be cautious in interpreting the effects as being the results of shifts in product demand. Instead, they can be regarded as the effects of changes in the demand for industry-specific skills.[20]

Comparison to Relative Wages Literature

The related studies using repeated cross-section analysis have typically examined the effects of industry demand shifts on wages by constructing demand shift measures for each group i as

$$\frac{\sum_j \alpha_{ij} \Delta E_j}{E_i},$$

where j indexes industry and α_{ij} is group i's share of total employment in efficiency units in industry j in the base year (see, for example, Katz and Murphy 1992; Bound and Johnson 1992; Blau and Kahn 1997). As mentioned earlier, the difficulty is quantitatively mapping changes in this index onto changes in relative wages.

Bound and Johnson (1992) reported the effects of product demand shifts on relative wages to be small and of uneven direction: they found that demand changes may explain 34% of the decline in the male/female wage gap but can only explain 8% of the increase in the male college/high school wage differential. Perversely, they found that demand changes actually reduced the rate of increase of the college/high school wage gap for women. Katz and Murphy (1992) did find strong movements of relative demand across industries and occupations favoring college graduates and women, but did not quantify the effects on relative wages. Blackburn, Bloom, and Freeman (1990) found that changes in final demand explain 20–30% of the widening of the earnings gap associated with education in the 1980s. Acs and Danziger (1996) also found modest effects of industry shifts on relative wages. Blau and Kahn (1997) found that industry demand shocks can

[19]Blau and Kahn (1997) found that the increase in the return to experience during the 1980s tended to increase the male-female wage gap. My analysis yields the opposite conclusion because I am following a cohort as they age and acquire experience, and the extra experience is more valuable to women than to men, given the lower level of initial experience for women and the concave wage-experience profile.

[20]Note that industry employment generally increased over this period, while real wages fell for some groups. This implies that industry employment cannot be interpreted as an absolute measure of demand shocks. For example, general population growth will tend to increase employment in most industries but will have both supply and demand effects in the labor market.

explain little of the convergence of the male-female wage gap.[21]

The industry demand effects I find for relative wages by education and by gender are larger than are typically reported in the literature. There are many possible reasons for these differences. First, it is likely that the explanations for changes in relative wages for a fixed group of people differ somewhat from the analysis in the literature, which typically compares the wages of individuals with similar age distributions over time. This is of particular relevance to the gender wage gap, as women's education and experience were rapidly improving over this period. Blau and Kahn (1997) showed that this is an important factor in explaining changes in the gender wage gap; it plays little role in my analysis because I follow a fixed sample of individuals. Thus, my within-cohort results should be seen as complementing results in the literature rather than contradicting them.

Second, my model fundamentally differs from that in the literature. In the shift-share approach, if a primarily male industry grows, this increases the demand for all men. My model has no concept of a demand for women or a demand for men, instead simply positing a demand for skills. Thus, the growth of this industry will increase the demand for individuals who have skills that are useful in this industry, whether they are male or female. If the growth of an industry increases the demand for all women, even those who are not marginal to it, that will not be picked up by my method, because controls for worker characteristics are incorporated in the estimation equation. Thus, results may differ because I do not capture group-level shocks to labor demand while the conventional approach follows a model that ignores the role of industry-specific skills.

Third, in my approach, the changes in industry employment are mapped onto changes in relative wages using the estimated coefficients from Table 3. In the shift-share approach, the results are strongly dependent on parameter values chosen to carry out the mapping. Thus, differences in the estimates may largely be a function of the parameter values used in the studies.

Conclusions

Using long differences in panel data, I find that industry growth and decline had a large effect on wages during the 1976–2001 period. Over 10-year periods, workers who were initially in industries that subsequently declined had slower wage growth than other workers. Furthermore, workers who, based on their education, sex, and industry affiliation at the beginning of the decade, were predicted to be likely to move to industries that subsequently declined had much slower wage growth than other workers. This suggests that some skills were neither industry-specific nor purely general in nature. The effects of industry demand changes on wages were larger for younger workers than for older workers but similar for men and women.

I used these estimates to predict how the relative wages of different groups by education, sex, and race were affected by changes in industry composition during the 1980s. A simple accounting scheme using the regression estimates suggests that changes in industrial composition can account for most of the within-cohort increase in the wages of women relative to those of men and 30–50% of the increase in the relative wage of more educated groups within cohorts. These effects are larger than those typically reported in studies that use repeated cross-sections to study changes in relative wages across cohorts. The smaller increase in the wages of whites compared to those of nonwhites cannot be explained by changes in industry demand.

The results have some interesting interpretations. They suggest that it is overly restrictive to describe skills as being either completely general or specific to one in-

[21]Bound and Freeman (1992) found large effects of demand shifts on the wages of young black men, especially in the Midwest. Bound and Holzer (1993) also found that industry shifts during the 1970s had modest negative effects on the earnings of young black men.

dustry.[22] Individuals can be seen as having a portfolio of skills that have different values in different industries. Shifts in labor demand across industries lead to changes in the value of the portfolio of skills. Blau and Kahn (1997) showed how the male-female wage gap closed during the 1980s despite the fact that women had fewer general skills than men (in terms of education and experience) and the return to general skills increased. My results suggest that although women had fewer general skills than men, their portfolios of industry-specific skills increased in value over the decade relative to those of men. This was an important factor in the reduction of the male-female wage gap over this period.

[22]However, Neal (1995) and Parent (2000) have shown that wages increase with industry-specific tenure, presumably because of investment in industry-specific skills.

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