Labor Market Conditions and Wage Determination: The Job-Loss Augmented Wage Curve

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For much of the mid- to late-1990s, economists have wondered at the simultaneously low unemployment and inflation rates in the United States. Since the fourth quarter of 1991, the Consumer Price Index has barely risen above three percent annually, falling below two percent for all of 1998.[2] Further, while wage inflation has increased slightly throughout the 1990s, it remained below four percent for 1998.[3] This despite the fact that the civilian unemployment rate in the US has fallen steadily from a high of 7.8 percent in June 1992 to 4.3 at the end of 1998.[4] This combination of a tight labor market with modest wage inflation and almost non-existent price inflation has led many to the conclusion that the Non-Accelerating Inflation Rate of Unemployment (NAIRU – alternatively known as the natural rate of unemployment) has fallen, allowing a permanent inward shift of the Phillips and wage-Phillips curves. A number of possible explanations for this shift have been suggested, including the increased use of temporary workers and increased price competition resulting from the abundance of information now available on the Internet. Each of these surely has some merit, but this paper

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[2] Federal Reserve Bank of New York web site: http://www.ny.frb.org/pihome/mktrates/indicators/cpi.pdf

[3] Bureau of Labor Statistics web site: http://146.142.4.24/cgi-bin/dsrv, Series ID: EES00500006

[4] Bureau of Labor Statistics web site: http://146.142.4.24/cgi-bin/surveymost, Series ID: LFS21000000

examines another possibility: that changes in job stability, as measured by job-loss rates within an industry, can explain the muted response of wages to low unemployment.

This possibility is suggested by recent trends in the measures of the conditions of the labor market. Rates of state unemployment and rates of industry job loss generally moved together through the 1980s and early 1990s, but around 1992, they diverged, with job-loss rates increasing while unemployment rates stayed low (Figure 1). It was at about this time that wage inflation became less responsive to the unemployment rate, leading logically to the hypothesis that it was, in fact, the job-loss rate that was driving wage inflation.

This paper, though, examines not only the effects on wage *inflation*, but also the effects on wages themselves. In 1994, David Blanchflower and Andrew Oswald suggested that the labor market determines not the rate of wage inflation, as the wage-Phillips curve claims, but rather determines the wage levels themselves (Blanchflower and Oswald 1994); this model they termed the wage curve. Building on this work, I evaluate the impact of job loss on wages.

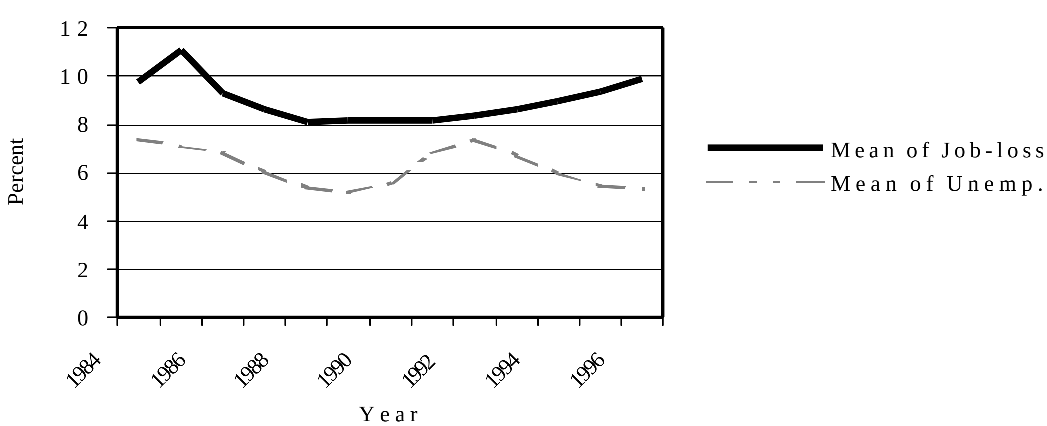

Figure 1: Industry Job-Loss Rates and State Unemployment Rates, 1984-1996

An intuitive mechanism for the connection between job loss and wage levels or wage inflation may be set forth immediately. It could easily be the case that low unemployment is found with high rates of job loss: if an industry or firm suffers, it may displace a large number of workers, but if other areas of the economy are strong enough to absorb these workers, the overall unemployment rate will remain low (the "Declining-Industry" hypothesis). The same conditions may be similarly found if the labor market becomes more volatile for any reason, with people switching jobs frequently (the "Employee-Turnover" hypothesis). However, if workers have a high cost associated with losing a job, the possibility of job loss may outweigh the ease of obtaining another job in the event of job loss in a tight labor market. In other words, workers may not want to or be able to change jobs for personal reasons even if it's fairly easy to do so, so in an environment of high job loss and low unemployment, they will not be as willing to demand a higher wage as they might when both unemployment and job loss are low.

My empirical findings seem to support this view. Using data from the Displaced Workers Surveys of 1984 through 1996, I find that, although job loss does not significantly improve the wage-Phillips curve's ability to predict or determine rates of wage inflation, job loss both improves the significance of unemployment and is strongly significant itself in the wage curve model, its two effects being to lower wage rates and weaken the sensitivity of wages to the rate of unemployment. Additionally, I find that the rate of industry job loss is a more consistent predictor of wages than is the rate of state unemployment, having a "job-loss elasticity of pay" at zero unemployment of –0.3 and an average job-loss elasticity of pay of –0.05 across several demographic variables.

Thus, while augmenting the wage-Phillips curve with job loss appears unnecessary, the job-loss augmented wage curve appears to be the correct model for assessing the wage-determining effects of the conditions of the labor market.

I. Job Loss and the Wage-Phillips Curve

Since my initial interest was in the combination of low unemployment and modest wage inflation, I present my findings on the effects of job-loss rates on the wage-Phillips curve first. My results show that these effects are not statistically significant: it cannot be said that job loss alters either wage inflation or the slope of the wage-Phillips curve. The presentation of these results is preceded by a description of my data and method.

A. Data and Method

To test the hypothesis that the rate of job loss lowers wage inflation and lessens the sensitivity of wage inflation to the unemployment rate (i.e., lowers the value of the slope of the wage-Phillips curve), I combine data from three different sources: the web site of the Bureau of Labor Statistics (BLS), the Annual Earnings File extract of the Current Population Survey (CPS), and the Displaced Workers Survey (DWS). The BLS web site provided seasonally adjusted unemployment rates for every state in every month from January 1978 to October 1998.[5] The unemployment rate obtained from the BLS web site is the standard definition: the number of unemployed at the time of the survey over the total size of the labor force. To avoid random noise in the data, I use the annual

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[5] These data may be found at http://stats.bls.gov/sahome.html, selecting "Local Area Unemployment Statistics," and proceeding with appropriate formatting choices (seasonally adjusted, state-level).

unemployment rate, calculated as the average of the 12 monthly rates for each state.

Job-loss rates are somewhat imprecise, being computed over a three-year period, because they are calculated from the Displaced Workers Survey. The DWS was a supplement to the January CPS in every second year from 1984 until 1994, when it was moved to the February CPS in every second year. The DWS asks a number of questions pertaining to job loss, but the two most important to this study are the questions asking if the respondent has lost a job in the previous three years and, if the answer is positive, from what industry the worker was displaced. Only those who have involuntarily lost a job are considered displaced workers by the DWS; displacement due to reasons specific to an individual, such as poor performance or voluntary departure, are not counted. By virtue of this fact, the rate of job loss that I use is more accurately indicative of the state of the labor market.

The industry from which the job was lost is recorded according to the Census Bureau's three-digit classification system,[6] a fact that allows job-loss rates to be calculated for every industry in every year of the survey. To reduce noise in the data, I calculate rates of job loss at a two-digit level, using only the first two digits of the three-digit classification.

In the actual calculation of rates of industry job loss, I adopt the definition used by Henry Farber in most of his work on rates of aggregate job loss (Farber 1998a, 1998b). Specifically, job loss is calculated as the number of people who report losing a job in the previous three years divided by the total number of people currently (that is, at the time of the survey) in the industry from which the job was lost. I use this method because it is

[6] See, for example, http://www.census.gov/apsd/techdoc/cps/mar97/append_a.html.

not computationally difficult and, as Farber notes (1998a, footnote 4), current employees represent "the pool of workers at risk to be displaced" and the very people whose wages are likely to be affected by job loss. Further, for the majority of the industry-year cells, the number of displaced workers is small relative to the current employment pool, in which case this method provides a good approximation of the risk facing current workers. Throughout this study, job-loss rates in excess of 100 percent were considered outliers and excluded from the analysis; in the wage-Phillips curve analysis, there were no such outliers.

The Annual Earnings File extract from the CPS forms the informational backbone of my study. The CPS is particularly useful for a study of this sort because of its size and comprehensiveness. It surveys approximately 60,000 households every month, providing a concise source of information on earnings, hours worked, and demographics. Further, with appropriate weighting, it is a representative sample of the U.S. population. For this study, AEF data for the years 1983 through 1996 were used and limited to males older than 16 years.

Once the earnings data from the thirteen CPSs are compiled, each observation is assigned a rate of job loss according to the year and two-digit industry category in which the worker is employed and a rate of unemployment according to the year and state in which the worker lives. Specifically, the relevant year is taken to be the year in which the job-loss and unemployment rates were calculated. Thus, a CPS observation from 1984 is assigned the change in his log wages from 1983 to 1984; the job-loss rate from the 1984 DWS, which was calculated using displacement over the years 1981 through 1983; and the unemployment rate calculated in 1984. This was done in part to compensate for an informational lag: job-loss rates are calculated after the fact, but wages or wage inflation is, if determined by this variable, affected by a similar lag. A worker in 1983 is most likely to have his wages, or the increase in his wages, in 1984 affected by the job-loss rate that prevails in 1983 but that is calculated in 1984. In the case of odd years – in which the DWS is not conducted and so rates of job loss not calculated – observations are assigned a job-loss rate equal to the mean of the job-loss rates of the years on either side. This is done in an effort to reflect the continuity of the changes in the labor market.

B. Results and Interpretations

The analysis of the wage-Phillips curve for males is done by regressing the change in log wages on the unemployment rate, the job-loss rate, the interaction of the unemployment and job-loss rates, and several demographic variables (education, experience, experience squared, and dummies for marriage, race, and union

Table 1: Wage-Phillips Curve, Males Only, 1984-1995

	Standard*					Augmented with Job Loss*			
Variable	**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**		**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**
Unemp. Rate (%)	-0.0054980	0.0007412	-7.418	0.000		-0.0065361	0.0010198	-6.409	0.000
Job Loss Rate (%)	n/a	n/a	n/a	n/a		-0.0007745	0.0005118	-1.513	0.130
(Job Loss)*(Unemp)	n/a	n/a	n/a	n/a		0.0001078	0.0000730	1.477	0.140
Marriage Dummy	-0.0081327	0.0018493	-4.398	0.000		-0.0081262	0.0018493	-4.394	0.000
Yrs. Education	0.0004427	0.0003163	1.400	0.162		0.0004415	0.0003163	1.396	0.163
Yrs. Experience	-0.0043712	0.0002112	-20.694	0.000		-0.0043703	0.0002112	-20.690	0.000
$(\text{Yrs. Exper.})^2$	0.0000581	0.0000041	14.144	0.000		0.0000581	0.0000041	14.138	0.000
Non-white Dummy	-0.0051625	0.0024892	-2.074	0.038		-0.0051336	0.0024893	-2.062	0.039
Union Dummy	0.0101967	0.0019300	5.283	0.000		0.0101562	0.0019302	5.262	0.000
			F(68, 292,001)=21.74					F(70, 291,999)=21.16	

*Both regressions include 11 year dummies, 50 state dummies (the District of Columbia being the 51st "state"), and a constant term not presented here. Both regressions also absorb the fixed effects of 88 industry categories.

membership). Additionally, dummies for every year but the first (to avoid collinearity) and every state but one are included to control for the fixed effects of those variables, and the fixed effects of industry category are absorbed in the regression. The standard wage-Phillips curve with demographic variables is first estimated, and then terms for job loss and the interaction of job loss and unemployment are added. The statistics of both regressions are presented in Table 1.

The results are not definitive, but are also not promising. Adding job loss to the equation increases the magnitude of the coefficient on unemployment. This result is consistent with the expectation that job loss lessens the sensitivity of males' wage inflation to the unemployment rate: the coefficient on unemployment in the augmented regression is the effect of unemployment on wage inflation when job loss is zero (a one percentage point increase in unemployment leads to a 0.6 percent increase in wage inflation when there is no job loss), whereas the coefficient in the standard model is the average effect of unemployment on wage inflation for all levels of job loss. Since the latter is smaller in absolute value, it stands to reason that job loss reduces the sensitivity of wage inflation to unemployment. Indeed, the direct evidence of this is the positive coefficient on the interaction term: as the rate of industry job loss increases, the effect of unemployment on wage inflation becomes less negative; the wage-Phillips curve is flattened by job-loss. Specifically, according to these results, a one percentage point increase in the job-loss rate will reduce the magnitude of the effect of unemployment by about 0.01 percentage points per percentage point of unemployment. Also in accord with expectations is the slightly negative coefficient on job-loss rate; a one percentage point increase in the rate of job loss will lower wage inflation directly by almost 0.08 percent.

However, the coefficients on job-loss rate and the interaction term have t-values of about 1.5 in absolute value; this means that there is a probability of 14 percent that job loss has no effect on wage inflation or the sensitivity of wage inflation to unemployment. While 14 percent is not especially bad, it is not as low as is standard to reject the null hypothesis – hence my statement that my results in adding job loss to the wage-Phillips curve are suggestive, but not definitive. I proceed to an analysis of the wage curve, which offers more promising results.

II. Job Loss and the Wage Curve

Initial results of my analysis of job loss and the wage curve are strongly supportive of a negative relationship between rates of industry job loss and males' wages. These initial results, which are further analyzed in Section III, are presented here, after a brief description of the data and method used for this analysis.

A. Data Summary

The data used for the wage curve analysis is essentially the same as that used in the wage-Phillips curve analysis. Data from 1984 through 1996 were used to compile a data set of over 953,000 observations.

Table 2: Means of Male Wage Curve Data by Year

Year	Mean of Job-loss	Mean of Unemp.	Mean of Log Wages
1984	9.790673	7.398215	2.111688
1985	11.053291	7.073474	2.150211
1986	9.317914	6.835528	2.180356
1987	8.597294	6.048716	2.208338
1988	8.116979	5.379462	2.233513
1989	8.145885	5.169221	2.277497
1990	8.150033	5.572982	2.325244
1991	8.147626	6.816756	2.356664
1992	8.377506	7.360536	2.375277
1993	8.642841	6.727079	2.396882
1994	8.954622	5.960510	2.429568
1995	9.402252	5.472466	2.459224
1996	9.883340	5.343778	2.460893

Brief summaries show that the average rate of job loss for all industries in all years is nine percent, the average unemployment rate for all states in all years is just over six percent, and the average log wage for all observations is 2.3. Table 2 shows the means of these variables for each year. It is difficult to see a relationship between wages and either of the labor market measures, partly because the wages are nominal, and so rise steadily over time (this is accounted for in the regression analyses by including a time trend). The data for the job-loss rate and unemployment rate in this data set are consistent with others' findings (e.g. Farber 1998a) in that the two measures move closely together until about 1992, when unemployment starts to decline but job loss continues to increase.

Table 3: Means of Job-Loss Rate by Year and Race

Year	Whites	Minorities
1984	9.874077	9.076775
1985	10.970541	11.720158
1986	9.374848	8.874973
1987	8.642433	8.244545
1988	8.145258	7.892108
1989	8.192139	7.788743
1990	8.205164	7.728818
1991	8.215785	7.638643
1992	8.469653	7.698686
1993	8.704227	8.212429
1994	9.007143	8.607434
1995	9.501885	8.802028

Table 4: Means of Job-Loss Rate by Year and Union Membership

Year	Non-Union	Union
1984	9.579623	10.455910
1985	10.823388	11.834883
1986	8.918806	10.742503
1987	8.253090	9.877391
1988	7.847916	9.163277
1989	7.915447	9.095332
1990	7.947271	8.983852
1991	7.898224	9.191935
1992	8.117399	9.501915
1993	8.257367	10.377771
1994	8.467426	11.183281
1995	9.101707	10.857539

Trends in the rate of industry job loss are also summarized by demographics. Table 3 shows job-loss rates for minorities and whites. In every year except 1985, whites have higher job-loss rates than minorities. This does not necessarily mean that whites are more frequently displaced than minorities, but it does mean that either whites work more frequently in industries that have high rates of job loss or minorities tend to concentrate in industries with lower rates of job loss. Union workers have higher rates of job loss for all years in the data set, as seen in Table 4. This is clearly expected, as it has already been seen that the industries with the highest rates of job loss are the "heavy" industries, which are also the industries that have the highest rate of unionization. The high job loss is almost surely a function of the industry and not of unionization. Both also follow the trend seen generally over time, although union workers have a slight decline in their rate of job loss in the last couple of years. This may be associated with the strong demand for manufactures in the boom economy of the middle 1990s, though even with this slight decline, the job-loss rate for union workers in the middle 1990s remains significantly higher than it was in the weak economy of 1990 and 1991.

C. Results and Interpretations

Much as in the analysis of the wage-Phillips curve, the standard wage curve is estimated by regressing log wages on unemployment, standard demographics (marriage, education, experience, race, and union status), and dummies to control for year and state fixed effects; industry fixed effects are absorbed in the regression. The wage curve is then augmented with job loss by adding the rate of job loss and the interaction of job loss and unemployment to the regression. The results of both regressions are presented in Table 5. In the standard wage curve specification, the results do not coincide with the results reported by Blanchflower and Oswald (1994). The unemployment rate is significant in determining wages, with a t-statistic of nearly 8, but the coefficient is positive: a one percentage point increase in the unemployment rate actually *raises* wages

Table 5: Wage Curve, Males Only, 1984-1996

	Standard*					**Augmented with Job Loss***			
Variable	**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**		**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**
Unemp. Rate (%)	0.0032282	0.0004127	7.823	0.000		-0.0014287	0.0005787	-2.469	0.014
Job Loss Rate (%)	n/a	n/a	n/a	n/a		-0.0032309	0.0002976	-10.855	0.000
(Job Loss)*(Unemp)	n/a	n/a	n/a	n/a		0.0004384	0.0000392	11.172	0.000
Marriage Dummy	0.1281651	0.0009405	136.277	0.000		0.1300244	0.0010245	126.920	0.000
Yrs. Education	0.0765390	0.0001591	481.209	0.000		0.0752228	0.0001747	430.509	0.000
Yrs. Experience	0.0341555	0.0001057	323.084	0.000		0.0335886	0.0001152	291.521	0.000
$(\text{Yrs. Exper.})^2$	-0.0005377	0.0000021	-251.93	0.000		-0.0005254	0.0000023	-226.001	0.000
Non-white Dummy	-0.1367526	0.0011868	-115.23	0.000		-0.1438932	0.0013058	-110.192	0.000
Union Dummy	0.1182141	0.0010416	113.496	0.000		0.1311177	0.0011598	113.055	0.000
	$F(69, 1{,}166{,}573)=9160.95$					$F(71, 952{,}882)=7104.63$			

*Both regressions include 12 year dummies, 50 state dummies (the District of Columbia being the 51st "state"), and a constant term not presented here. Both regressions also absorb the fixed effects of 88 industry categories.

by just over 0.3 percent. This is in direct opposition to Blanchflower and Oswald's finding that unemployment lowers wages by about 0.1 percent per point, though admittedly, Blanchflower and Oswald estimated their results for both genders, making it difficult to compare their results with these. For men, though, when this result is combined with the strong results of unemployment's effects on wage inflation, the findings suggest support of the traditional Phillips curve over the standard wage curve.

When job-loss rates and the interaction are added to the model, however, a clearer picture develops. The coefficient on unemployment becomes significantly negative, with a t-statistic of about –2.5 and an "elasticity of pay" (as Blanchflower and Oswald term the effect of unemployment on wages) for unemployment of –0.14, quite close to Blanchflower and Oswald's findings. However, this value is the effect of unemployment only when job loss is zero. The realized effect will be the effect at the mean rate of job loss. This effect is quite different because, as this paper set out to show, *the effects of unemployment change as the job-loss rate changes*.

Most important to this study is the fact that both the job-loss rate and the interaction term are significant and have signs consistent with my expectations. Specifically, job loss per se lowers wages by an estimated 0.3 percent per percentage-point increase in the job-loss rate, a strongly significant result. The interaction of job loss and unemployment has a positive coefficient and a high t-statistic. Practically, this means that, as predicted, *increasing the rate of job loss lowers the sensitivity of wages to unemployment*. Every percentage point of job loss makes the unemployment elasticity of pay (to distinguish from the job-loss elasticity of pay) more positive by 0.04 points. At zero job loss, then, the unemployment elasticity of pay is about –0.14, but at a rate of job loss of one percent, this declines to –0.10, at two percent to –0.06, and so on. As noted above, the realized effect of unemployment will occur at the mean of job loss. With a mean rate of job loss of roughly nine percent, the unemployment elasticity of pay will be positive – about 0.22, not dissimilar from the result obtained by estimating the wage curve without controlling for job loss.

These results imply, in fact, that for any industry job-loss rate over roughly 3.5 percent, the unemployment elasticity of pay will be positive in that industry. Whereas the result found by Blanchflower and Oswald predicts that wages will be higher in periods of low unemployment, the result found here predicts that wages will be higher in periods of low unemployment *only if the job-loss rate is also low*. With high rates of job loss, not only are wages lowered by the job loss directly, but the effect of low unemployment (which would tend to raise wags) is lessened. Indeed, with sufficiently high rates of job loss, the unemployment-wage relationship becomes positive, so that a decline in unemployment will serve to lower wages further, reinforcing the wage-decreasing effect of high job loss.

While this conclusion does not translate directly to the recent combination of low unemployment and modest wage *inflation* that generated the initial interest of this study, it has obvious implications for it. Furthermore, even if this result does not answer my original question directly, it is immensely interesting in its own right. Finding a job-loss elasticity of pay of –0.3 suggests that the labor market may determine wages in ways not previously considered.

III. Other Wage Curve Considerations

Several explanations other than a direct causal relationship could account for the strong effects found. In this section, I examine some of these possibilities and reject them as alternatives in an attempt to strengthen the argument that job loss itself causes wages to be lower and less sensitive to unemployment. This is done with respect to the following: first, compositional biases, the notion that the demographic composition of the labor force in an industry will affect its wages; second, declining industries, as opposed to employee turnover (see p. 3); third, inaccurate standard errors; and fourth, variations in the specification of the job-loss augmented wage curve.

A. Compositional Biases

One potential explanation of the observed effect of job loss on wages and the unemployment elasticity of pay is that the industries with high job-loss rates are undergoing changes in the composition of their labor forces. If the displaced workers are disproportionately members of demographic groups that typically have higher wages, it may be the case that wages are being lowered not by the job loss itself, but by the change in the composition of the industry's labor force to include a larger percentage of lower-wage workers. A study of this possibility is done here by looking at two demographic variables, union membership and minority status (an obvious third choice would be gender if these results were found in data for both sexes).

The same job-loss augmented wage curve specification is estimated, but with the omission first of the union dummy variable and second of the non-white dummy variable. The results of omitting the union dummy are presented in Table 6, with the full model presented as a point of comparison; the results of omitting race are similarly presented in

Table 6: Omission of Union from Male Wage Curve, 1984-1996

	Augmented with Job Loss*					Union Dummy Omitted*			
Variable	**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**		**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**
Unemp. Rate (%)	-0.0014287	0.0005787	-2.469	0.014		-0.0013983	0.0005825	-2.400	0.016
Job Loss Rate (%)	-0.0032309	0.0002976	-10.855	0.000		-0.0033795	0.0002996	-11.279	0.000
(Job Loss)*(Unemp)	0.0004384	0.0000392	11.172	0.000		0.0004550	0.0000395	11.518	0.000
Marriage Dummy	0.1300244	0.0010245	126.920	0.000		0.1312131	0.0010313	127.236	0.000
Yrs. Education	0.0752228	0.0001747	430.509	0.000		0.0737240	0.0001754	420.341	0.000
Yrs. Experience	0.0335886	0.0001152	291.521	0.000		0.0348242	0.0001155	301.598	0.000
$(\text{Yrs. Exper.})^2$	-0.0005254	0.0000023	-226.001	0.000		-0.0005448	0.0000023	-233.457	0.000
Non-white Dummy	-0.1438932	0.0013058	-110.192	0.000		-0.1361265	0.0013127	-103.696	0.000
Union Dummy	0.1311177	0.0011598	113.055	0.000		n/a	n/a	n/a	n/a

F(71, 952,882)=7104.63 F(70, 952,883)=6930.57

*Both regressions include 12 year dummies, 50 state dummies (the District of Columbia being the 51st "state"), and a constant term not presented here. Both regressions also absorb the fixed effects of 88 industry categories.

Table 7. The omission of the union dummy has little effect on the coefficient of the rate of job loss, though it lowers it slightly (which is equivalent to saying that it augments the effect of job loss). If it were the case that union workers were being displaced disproportionately and that this, not the job loss itself, were depressing wages (since union membership tends to raise wages), then there would be a positive correlation between rates of job loss and union status: job-loss rates would be higher in those industries with large numbers of workers under union contracts and decline as fewer union workers were left in the industry. Since the coefficient on union status is positive, the omission of union status from the regression would lead to a positive bias in the coefficient on job-loss rates, that is, that coefficient would be higher in the omitted-variable regression. This is not the case; the coefficient is lower, although so slightly so that the difference is surely not significant. Therefore, it appears that a decline in

Table 7: Omission of Race from Male Wage Curve, 1984-1996

Variable	Augmented with Job Loss* Coefficient	Std. Error	t-stat	P>|t|		Non-White Dummy Omitted* Coefficient	Std. Error	t-stat	P>|t|
Unemp. Rate (%)	-0.0014287	0.0005787	-2.469	0.014		-0.0015406	0.0005823	-2.646	0.008
Job Loss Rate (%)	-0.0032309	0.0002976	-10.855	0.000		-0.0031998	0.0002995	-10.683	0.000
(Job Loss)*(Unemp)	0.0004384	0.0000392	11.172	0.000		0.0004338	0.0000395	10.986	0.000
Marriage Dummy	0.1300244	0.0010245	126.920	0.000		0.1363084	0.0010294	132.419	0.000
Yrs. Education	0.0752228	0.0001747	430.509	0.000		0.0758572	0.0001757	431.634	0.000
Yrs. Experience	0.0335886	0.0001152	291.521	0.000		0.0333040	0.0001159	287.299	0.000
$(\text{Yrs. Exper.})^2$	-0.0005254	0.0000023	-226.001	0.000		-0.0005198	0.0000023	-222.227	0.000
Non-white Dummy	-0.1438932	0.0013058	-110.192	0.000		n/a	n/a	n/a	n/a
Union Dummy	0.1311177	0.0011598	113.055	0.000		0.1243945	0.0011655	106.729	0.000

$F(71, 952{,}882)=7104.63$ $F(70, 952{,}883)=6944.18$

*Both regressions include 12 year dummies, 50 state dummies (the District of Columbia being the 51st "state"), and a constant term not presented here. Both regressions also absorb the fixed effects of 88 industry categories.

unionization is not responsible for the observed effect of job-loss rates on wages and the unemployment elasticity of pay.

Omitting the non-white dummy variable (Table 7) has a similarly negligible effect on the estimated coefficients in the wage curve regression. Since non-white workers are, on average, paid less than white workers, it would have to be white workers losing their jobs in order for job loss to appear to be lowering wages. In that case, job loss should be most common in industries with low percentages of non-white workers, creating a negative correlation between job-loss rates and being a minority. With both a negative covariance and a negative coefficient on the non-white dummy, the bias generated by omitting that variable should be positive. Again, though, while the coefficient is apparently larger, the difference is not significant. An increasing racial diversification of the labor force is thus also not the cause of the observed effects of job-loss rates on males' wages.

While many other potential compositional biases that could be driving this result surely exist, these two – unionization and race – are two of the most likely, given their plausibility under recent trends in the labor force and their significant effects on wages (again, the third likely factor, gender, was deliberately eliminated at the beginning of the study). With these two possibilities eliminated, it is much safer to say that the negative effect of job loss is not due to a systematic shift in the composition of the labor force.

B. Declining Industries v. Employee Turnover

As suggested earlier, high rates of job loss may indicate one of two conditions: either the labor demand in an industry as a whole is declining, so that workers are being displaced without being replaced; or the industry is characterized by high employee turnover, so that workers are replaced with new workers as they are displaced. If the former case dominates, then my results are somewhat less interesting, since displaced workers would have to find employment in different industries and most likely in industries in which they have less expertise – which would naturally depress wages. Job loss would not be directly responsible for the wage decline.

This could be an argument for the use of a measure of industry-specific training or experience, rather than the general experience measure used here, but such an industry-specific measure is not available from the CPS. Instead, I estimate trends in turnover by looking at employment levels in each industry based on males' CPS responses from 1984 through 1996. If employment levels decline significantly, this is evidence that the industry is declining, or at least in the trough of a cyclical employment pattern, which would have the same effects. Hence, to say as I want that the job-loss rate is directly responsible for the effect on wages, such a decline must be ruled out as a general pattern. Employment in an industry was calculated both as an absolute figure – the number of people who reported being employed and working in that industry – and as a percentage of all employed people in the labor force, providing a measure of relative decline.

If I were to find a strong correlation between the rate of job loss and either of the measures of industry employment, then I would have to say that job loss could be indicating a declining industry rather than employee turnover. This is not the case, though. The rate of job loss is, in fact, only weakly correlated with either measure, if at all. The coefficient of correlation between the rate of job loss and the number of employees in an industry is found to be 0.1139, and the coefficient between the rate of job loss and the employment percentage in an industry is found to be only 0.1217. With these figures, it is safe to conclude that job loss does not move closely with industry employment. It is not capturing the effects of an industry's decline.

It is also possible to judge the effects of declining industries on the job-loss augmented wage curve by excluding those industries from the regression analysis. The employment percentage is used as the evaluative statistic for this purpose because only relative declines would affect the impact of job loss on wages; if all industries are declining, as could be captured by levels of employment, either unemployment is increasing, which has an effect on wages that is not the point of this study, or the labor force is shrinking, which should lead to higher wages, not the lower wages that are correlated with a higher rate of job loss. It can be found that the largest declines over the period in question came in Machinery and Computing Equipment and Mining. Results of the regression that excludes these declining industries are shown in Table 8, again with

Table 8: Male Wage Curve, Excluding Declining Industries, 1984-1996

	Augmented with Job Loss*					Declining Industries** Excluded*			
Variable	**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**		**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**
Unemp. Rate (%)	-0.0014287	0.0005787	-2.469	0.014		-0.0014629	0.0006092	-2.401	0.016
Job Loss Rate (%)	-0.0032309	0.0002976	-10.855	0.000		-0.0029132	0.0003262	-8.931	0.000
(Job Loss)*(Unemp)	0.0004384	0.0000392	11.172	0.000		0.0003851	0.0000439	8.764	0.000
Marriage Dummy	0.1300244	0.0010245	126.920	0.000		0.1312746	0.0010660	123.147	0.000
Yrs. Education	0.0752228	0.0001747	430.509	0.000		0.0740507	0.0001827	405.415	0.000
Yrs. Experience	0.0335886	0.0001152	291.521	0.000		0.0334577	0.0001200	278.868	0.000
(Yrs. Exper.)^2	-0.0005254	0.0000023	-226.001	0.000		-0.0005244	0.0000024	-216.606	0.000
Non-white Dummy	-0.1438932	0.0013058	-110.192	0.000		-0.1451385	0.0013491	-107.581	0.000
Union Dummy	0.1311177	0.0011598	113.055	0.000		0.1334708	0.0012096	110.344	0.000

F(71, 952,882)=7104.63 F(71, 879,690)=6456.35

*Both regressions include 12 year dummies, 50 state dummies (the District of Columbia being the 51st "state"), and a constant term not presented here. Both regressions also absorb the fixed effects of 88 industry categories.

**As determined by employment percentage, i.e. employees in an industry as a percentage of employed people in the total labor force.

the previously estimated job-loss augmented wage curve results alongside for comparison. The important result is that the coefficients on the three test variables and their levels of significance are not much different; the job-loss rate still depresses wages by about 0.3 percent at zero unemployment (by 0.06 percent at the mean unemployment rate) and changes the unemployment elasticity of pay by 0.04 points per point of job loss. Decline in employment in the industries is apparently not responsible for the effect of the job-loss rate.

C. Recalculated Standard Errors

In the previous analyses, the effects of job loss are found to be significant based on the standard t-statistics of the coefficients on the rate of job loss and on the interaction of unemployment and job loss. However, the standard errors used in the calculation of these t-statistics have a potential problem similar to one of the points that David Card notes in his (1995) review of Blanchflower and Oswald's book, *The Wage Curve*. These standard errors are based on the number of individual observations, but as Card writes, "the actual 'degrees of freedom' involved in the estimation of the wage curve elasticity is far less than the number of individual wage observations. Indeed, the relevant dimension for the estimation of the unemployment coefficient is the number of regional labor markets times the number of time periods" (p. 7). In other words, standard errors must be calculated at the smallest level of variation in the relevant variable. In this study, all individuals in the same year and industry have the same rate of job loss, all in the same year and state have the same rate of unemployment, and all in the same year-state-industry cell have the same value for the interaction term. Calculating standard errors at the individual level will therefore lead to a large downward bias in those errors, which leads to t-statistics that will overstate the significance of those variables.

One solution to this problem – and the one adopted here – is to collapse the data onto the mean of the variables within the state-industry-year cell. This aggregation method is quite similar to Blanchflower and Oswald's approach to this problem, and is good in that it accounts for most of the bias in the standard errors and is fairly simple to do. It is not ideal, though, since this method can lead to imprecise estimates of the coefficients on the control variables. It will also alter the coefficients of the test variables if the cells are not weighted by the number of observations in each; cells with many observations will have the same impact on the results as cells with few observations if they are merely collapsed onto their means without weighting. This weighting is not difficult, and is used here, so all coefficients presented in the tables are valid for analysis. Some discrepancy between the aggregated-data and individual-data coefficients remains, but this method works well for judging the bias in the standard errors of the variables this study is most interested in.

Using this aggregation method on the standard wage curve and the job-loss augmented wage curve leads to the results presented in Table 9 (next page). For comparison, I have reproduced beside it Table 5, which shows the same results for the original, uncollapsed data. In the case of the standard wage curve, observations are aggregated over the larger state-year cells, rather than state-year-industry cells, since no variation occurs across industry categories. This leads to insignificance in some of the demographic variables, but this may be due to the imprecision in the control variables that Card noted. This also accounts for the fact that the standard errors of the augmented model are smaller than in the standard wage curve model. Note, though, that the standard errors for the collapsed data are larger in all cases than the corresponding figures for the uncollapsed data (comparing the standard errors in Table 9, which uses collapsed data, with those in Table 5).

The result that is consequential to this study is the fact that both the job-loss rate and the interaction are still significant at less than one percent, even with the larger standard errors. They also still have the expected sign, and the effects, as they should be, are roughly the same. An additional percentage point in the job-loss rate still lowers wages by about 0.3 percent at zero unemployment (again, the effect at the mean unemployment rate is about 0.06 percent) and lowers the magnitude of the unemployment elasticity of pay by about .04 percentage points. The same result holds for the unemployment rate in the job-loss augmented model, as it is significant and consistent with the idea of the wage curve at zero job loss, though the unemployment

Table 9: Male Wage Curve, Adjusted Standard Errors,** 1984-1996

	Standard Model* (with collapsed data)					Augmented with Job Loss* (with collapsed data)			
Variable	**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**		**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**
Unemp. Rate (%)	0.0025857	0.0010721	2.412	0.016		-0.0027540	0.0006713	-4.102	0.000
Job Loss Rate (%)	n/a	n/a	n/a	n/a		-0.0029557	0.0003247	-9.102	0.000
(Job Loss)*(Unemp)	n/a	n/a	n/a	n/a		0.0004419	0.0000451	9.794	0.000
Marriage Dummy	0.1560842	0.0836257	1.866	0.062		0.1492393	0.0054125	27.573	0.000
Yrs. Education	0.1153201	0.0097663	11.808	0.000		0.0945514	0.0007938	119.107	0.000
Yrs. Experience	-0.0135744	0.0100055	-1.357	0.175		0.0360694	0.0005847	61.684	0.000
(Yrs. Exper.)^2	0.0000894	0.0002109	0.424	0.672		-0.0005849	0.0000118	-49.487	0.000
Non-white Dummy	-0.1962565	0.0835755	-2.348	0.019		-0.1403055	0.0063632	-22.050	0.000
Union Dummy	0.1568507	0.0869107	1.805	0.072		0.2259378	0.0046854	48.221	0.000

F(69, 593)=350.75 F(71, 44,503)=1458.01

*Both regressions include 12 year dummies, 50 state dummies (the District of Columbia being the 51st "state"), and a constant term not presented here. Both regressions also absorb the fixed effects of 88 industry categories.

**Standard errors are adjusted by aggregating the observations over state-year cells for the standard wage curve and over state-year-industry cells for the job-loss augmented wage curve.

Table 5: Wage Curve, Males Only, 1984-1996

	Standard*					Augmented with Job Loss*			
Variable	**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**		**Coefficient**	**Std. Error**	**t-stat**	**P>|t|**
Unemp. Rate (%)	0.0032282	0.0004127	7.823	0.000		-0.0014287	0.0005787	-2.469	0.014
Job Loss Rate (%)	n/a	n/a	n/a	n/a		-0.0032309	0.0002976	-10.855	0.000
(Job Loss)*(Unemp)	n/a	n/a	n/a	n/a		0.0004384	0.0000392	11.172	0.000
Marriage Dummy	0.1281651	0.0009405	136.277	0.000		0.1300244	0.0010245	126.920	0.000
Yrs. Education	0.0765390	0.0001591	481.209	0.000		0.0752228	0.0001747	430.509	0.000
Yrs. Experience	0.0341555	0.0001057	323.084	0.000		0.0335886	0.0001152	291.521	0.000
(Yrs. Exper.)^2	-0.0005377	0.0000021	-251.93	0.000		-0.0005254	0.0000023	-226.001	0.000
Non-white Dummy	-0.1367526	0.0011868	-115.23	0.000		-0.1438932	0.0013058	-110.192	0.000
Union Dummy	0.1182141	0.0010416	113.496	0.000		0.1311177	0.0011598	113.055	0.000

F(69, 1,166,573)=9160.95 F(71, 952,882)=7104.63

*Both regressions include 12 year dummies, 50 state dummies (the District of Columbia being the 51st "state"), and a constant term not presented here. Both regressions also absorb the fixed effects of 88 industry categories.

elasticity of pay here is somewhat larger than that estimated by Blanchflower and Oswald (1994). With a positive and significant coefficient on the interaction term, this observed negative effect of the unemployment rate will get smaller as the rate of industry job loss increases, so that at the mean rate of job loss, the effect of unemployment is zero or positive, which is not consistent with the wage curve.

The significance of the test variables in this analysis is a crucial result. Even with the upwardly adjusted standard errors, the effects of the rate of job loss on both wages and the unemployment elasticity of pay are strongly significant, a fact that makes my conclusion – that the rate of industry job loss is as important a measure of the state of the labor market as the state unemployment rate is – much stronger.

D. Variations in the Effects of the Job-Loss Rate

The effects of the rate of job loss on males' wages may be altered by a number of variables. This section presents some descriptive data (descriptive in that the differences are not rigorously tested in most cases) of the differences in those effects across several demographic variables. It must be noted beforehand that, in investigating the differences across demographic groups, other demographic variables are excluded. This omission has at most a negligible bearing on this discussion.

D.1. MINORITY V. WHITE

When the data are divided on the basis of minority status, we see that the effects of the job-loss rate are roughly the same for whites and minorities, but the wages of minorities are much more responsive to the unemployment rate than are those of white workers (Table 10). Also, the job-loss elasticity of pay at zero unemployment is again

Table 10: Male Wage Curve, By Minority Status, Adjusted Standard Errors, 1984-1996**

	Whites*					Minorities*			
Variable	Coefficient	Std. Error	t-stat	P>|t|		Coefficient	Std. Error	t-stat	P>|t|
Unemp. Rate (%)	-0.0005764	0.0008996	-0.641	0.522		-0.0052328	0.0019853	-2.636	0.080
Job Loss Rate (%)	-0.0035571	0.0004331	-8.214	0.000		-0.0034740	0.0009964	-3.486	0.000
(Job Loss)*(Unemp)	0.0005471	0.0000603	9.075	0.000		0.0005069	0.0001368	3.704	0.000
	F(142, 43,755)=1357.27					F(142, 23,406)=267.75			

*Both regressions include 12 year dummies, 50 state dummies (the District of Columbia being the 51st "state"), 87 industry dummies, and a constant term not presented here.

**Standard errors are adjusted by aggregating the observations over state-year cells for the standard wage curve and over state-year-industry cells for the job-loss augmented wage curve.

around –0.3, and is around –0.05 at the mean rate of unemployment, a result that appears regardless of how the data is divided. It might have been expected that wages of minorities are less responsive to unemployment, since the racial wage gap has been generally decreasing over the past few decades, suggesting that minorities' wages would be less subject to the depressing effects of unemployment, but just the opposite appears to be true. Why this should be the case is not at all clear. Regardless, the result remains that the rate of job loss is a more consistent predictor of wages than the rate of unemployment across demographic groups.

D.2. WHITE-COLLAR V. BLUE-COLLAR

The effects of job loss change when the data are divided by occupation type (Table 11). While white-collar workers are more affected by their state unemployment rate, the industry job-loss rate has a smaller effect on their wages than on blue-collar wages. In fact, at zero unemployment, a percentage point in the job-loss rate lowers wages for white-collar workers by roughly 0.25 percent, but lowers them for blue-collar workers by 0.44 percent. Similarly, the unemployment elasticity of pay is altered more

Table 11: Male Wage Curve, By Occupation Type, Adjusted Standard Errors, 1984-1996**

Variable	Blue Collar* Coefficient	Std. Error	t-stat	P>|t|		White Collar* Coefficient	Std. Error	t-stat	P>|t|
Unemp. Rate (%)	-0.0018733	0.0010507	-1.783	0.075		-0.0022900	0.0010917	-2.098	0.036
Job Loss Rate (%)	-0.0044092	0.0004967	-8.878	0.000		-0.0025477	0.0005468	-4.659	0.000
(Job Loss)*(Unemp)	0.0006397	0.0000692	9.241	0.000		0.0004125	0.0000760	5.431	0.000
	F(142, 39,506)=844.13					F(142, 39,592)=1232.78			

*Both regressions include 12 year dummies, 50 state dummies (the District of Columbia being the 51st "state"), 87 industry dummies, and a constant term not presented here.

**Standard errors are adjusted by aggregating the observations over state-year cells for the standard wage curve and over state-year-industry cells for the job-loss augmented wage curve.

dramatically for blue-collar workers, 0.06 points compared to 0.04, so that the average effect of job loss is –0.08 percent for blue-collars and basically zero for white.

This difference suggests that the wages of white-collar workers are generally less susceptible to labor market pressures. Management positions may generally receive longer-term contracts, perhaps because they are seen as more vital to the firm. Another possibility is that the wages captured by the CPS are only base salary and not total compensation. Bonuses and other performance-based pay, which are larger components of white-collar compensation than blue-collar, may be more strongly correlated with labor market conditions.

D.3. EDUCATION CATEGORY

Dividing by education category leads to some slightly different results (Table 12). The first three categories – less than high school, high school only, and less than four years of college – follow a pattern similar to that of the above demographic groupings. The job-loss effects are significant in all three cases, though they are somewhat mitigated for those with some college, and the unemployment rate is significant at less than 10 percent in all cases, with the wages of those with only a high school diploma affected somewhat less strongly by unemployment than the other two categories.

Once a four-year college diploma is obtained, however, the relationship between these labor market measures and wages collapses. The unemployment rate is the strongest, and even that barely has a confidence level of 80 percent. This marks the first group for which the job-loss rate does not significantly determine wages. Unemployment also has a much weaker effect than before, and may even positively affect wages. To some extent, this might be expected. Highly educated people are more likely to be in jobs that are less susceptible to labor market conditions. If education is viewed as a form of general training, those with more education are more valuable to the firm in terms of productivity, and so are less likely to be displaced even in an environment of high job-

Table 12: Male Wage Curve, By Education Category, Adjusted Standard Errors, 1984-1996**

	Less Than High School*					High School Diploma*			
Variable	Coefficient	Std. Error	t-stat	P>|t|		Coefficient	Std. Error	t-stat	P>|t|
Unemp. Rate (%)	-0.0039034	0.0015009	-2.601	0.009		-0.0018132	0.0010890	-1.665	0.096
Job Loss Rate (%)	-0.0047148	0.0007437	-6.339	0.000		-0.0045674	0.0005237	-8.721	0.000
(Job Loss)*(Unemp)	0.0006056	0.0001014	5.975	0.000		0.0006617	0.0000724	9.139	0.000
	F(142, 30,604)=411.86					F(142, 39,284)=655.77			

	Some College*					Four-Year College Diploma*			
Variable	Coefficient	Std. Error	t-stat	P>|t|		Coefficient	Std. Error	t-stat	P>|t|
Unemp. Rate (%)	-0.0032023	0.0014606	-2.192	0.028		0.0021422	0.0016043	1.335	0.182
Job Loss Rate (%)	-0.0034320	0.0007281	-4.713	0.000		0.0002225	0.0007464	0.298	0.766
(Job Loss)*(Unemp)	0.0005122	0.0001032	4.965	0.000		0.0000179	0.0001040	0.172	0.863
	F(142, 35,075)=451.07					F(142, 31,578)=283.32			

*All regressions include 12 year dummies, 50 state dummies (the District of Columbia being the 51st "state"), 87 industry dummies, and a constant term not presented here.

**Standard errors are adjusted by aggregating the observations over state-year cells for the standard wage curve and over state-year-industry cells for the job-loss augmented wage curve.

loss rates. With less risk, their wages will not suffer the same negative effects of a slack labor market. Indeed, because they are more valuable to the firm, employers will be more willing to give longer-term contracts specifically because the value to the firm of highly trained workers will not change with the cycles of the economy, whereas a worker who is only marginally beneficial in a strong economy is at great risk if the firm finds it necessary to cut costs in a weak economy. With longer-term contracts, then, the wages of highly educated people will be less procyclical, which is precisely the result obtained here.

IV. Conclusion

This study has attempted to redefine the wage-Phillips curve and the wage curve, as first proposed by Blanchflower and Oswald (1994), by augmenting both models with a second measure of the prevailing conditions in the labor market: the rate of job loss within an industry. Success for the wage-Phillips curve is little if any, but the wage curve results are much stronger. Surely, my results can only be regarded as preliminary, but they are definitive within the scope of this study, and seem to support expanding the scope. The major results found here may be summarized as follows:

1. The job-loss augmented model of the wage-Phillips curve cannot be supported, as the rate of industry job loss does not appear to determine or predict wage inflation. Job-loss rates are only weakly, if at all, significant in a wage-Phillips curve for males.
2. The job-loss augmented model of the wage curve is strongly supported. The rates of industry job loss have a significant and negative effect on males' wages and a significant and positive effect on the unemployment elasticity of pay (as defined by

Blanchflower and Oswald (1994)). As the unemployment elasticity of pay is negative, this means that industry job loss weakens the negative sensitivity of males' wages to state unemployment.

3. The estimated job-loss elasticity of pay at zero unemployment is consistently around –0.3. The average effect of job loss, that is, the job-loss elasticity of pay at the mean rate of unemployment, is consistently around –0.05. This is true across several demographic variables, including union status, race, and marital status.[7]
4. Across these demographic variables, the rate of industry job loss is a much more consistent predictor of wages than is the rate of state unemployment, as the job-loss elasticity of pay remains about the same in all cases, while the unemployment elasticity of pay varies greatly.
5. The job-loss elasticity of pay does vary across education levels, experience levels, occupation types, and industry categories.[7] Specifically, those with more education or more experience are insulated from the effects of both industry job loss and state unemployment on their wages, consistent with the hypothesis that the accumulation of human capital lessens the susceptibility of one's wages to labor market conditions. White-collar workers are also less affected in their wages by the tightness of the labor market, though the effects on other types of compensation, such as bonuses, are not studied here.
6. The effects of job loss, both on wages and on the unemployment elasticity of pay, remain significant at less than 0.1 percent (a confidence level of 99.9 percent associated with t-statistics of over nine in both cases) and the coefficients change

[7] To conserve space, the analysis of some of these demographic variables has not been included. For full results, contact the author.

little when standard errors are adjusted by collapsing the data on to means within state-year-industry cells.

7. The observed effects of rates of industry job loss do not appear to be caused by changes in the racial composition (looking at whites versus non-whites) of the labor force within an industry or by changes in an industry's rate of unionization.
8. The observed effects of rates of industry job loss also do not appear to be caused by a decline in the size of an industry's labor force, suggesting that the measured rate of job loss is instead correlated with employee turnover.

Future studies may endeavor to examine the differences between actual rates of industry job loss, which I have used here, and perceptions of job security. While actual job loss produces strong results in a wage curve model, it may be that perceptions of job security come closer to explaining the observation I originally sought to understand, the combination of low rates of unemployment and modest wage inflation. Some work in this area has already been done by Daniel Aaronson and Daniel G. Sullivan (1999), who conclude in a study published just before the completion of this one that "variations in displacement rates and anxiety levels" may be sufficient to explain "all or most of the puzzle of slow wage growth in the 1990s" (p. 39). Even if Aaronson and Sullivan's work is not definitive on the subject, it may be as close as we get to the answer to a question that involves such amorphous variables as worker anxiety. That, of course, is the benefit of using job-loss rates alone. While they do not appear to explain changes in the wage-Phillips curve without including measures of anxiety, they clearly have a strong impact on the wage curve.

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