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Does Monetary Policy Affect Relative Educational Unemployment Rates?

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By PHILIP N. JEFFERSON*

> *To some extent, the lingering pattern of unemployment after growth resumes, especially among the less skilled, is inadvertently reinforced by the major policy tool used to lift the economy out of recession—interest rate cuts by the Federal Reserve.*
>
> —Alan B. Krueger (2002)

This paper examines the empirical relationship between relative educational unemployment rates and monetary policy. Such an examination is warranted because policymakers' attempts to understand the distributional effects of monetary policy may be confounded by vintages of the theoretical literature that offer contrasting views of how skill-based relative unemployment (with unemployment of the less skilled in the numerator) might behave over the business cycle.

A traditional view emphasizes characteristics of labor markets that could induce countercyclical movements in skill-based relative unemployment. For example, Arthur Okun (1973) argues that an important benefit of high levels of aggregate economic activity is that opportunities for employment in the high-quality jobs sector open up to the relatively unskilled. A mechanism for the relative improvement of the employment prospects of the unskilled is changes in hiring standards of high-quality job providers that occur over the cycle. Changes that occur during expansion and boom periods mentioned by Okun include accepting younger and less experienced workers or workers without diplomas and more intensive screening of applicants. A forceful statement of this high-pressure economy view is contained in Rebecca Blank (2000).

A more recent view of the impact of technological adoption could have quite different implications for movements in skill-based relative unemployment over the cycle. For example, Dale Mortensen and Christopher Pissarides (1999) show that, in their equilibrium search and matching framework, the relationship between skill and unemployment is convex in the presence of labor-market policies such as unemployment compensation. In this environment, skill-biased technology shocks increase overall unemployment rates with a disproportionate share of the unemployment falling on the unskilled. In his popular account of the matter, Krueger (2002) ties cyclical investment in new technologies to the conduct of monetary policy, thereby linking relative educational unemployment to monetary policy.

My answer to the title question emerges from quantitative results designed to assess the dynamic effect on relative educational unemployment of a monetary policy surprise, controlling for supply shocks and the introduction of new technical ideas. These findings appear to resolve some of the tension between alternative views on relative unemployment dynamics in favor of the high-pressure economy hypothesis.

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TABLE 1—RELATIVE UNEMPLOYMENT RATES: SUMMARY STATISTICS 1992:1–2003:12

Education level	Mean	SD
Dropouts/College	3.603	0.463
High School/College	2.015	0.183
Some College/College	1.636	0.142
Dropouts/Some College	2.203	0.247
High School/Some College	1.233	0.087
Dropouts/High School	1.785	0.139

Note: SD = standard deviation.

I. Relative Unemployment: Some Facts

Monthly data on unemployment by educational attainment are available from the Bureau of Labor Statistics. Data for four levels of educational attainment are reported for the civilian population age 25 and older: less than high-school diploma (Dropouts), high-school diploma but no college (High School), some college and/or associate's degree (Some College), and bachelor's degree or better (College). I work with the seasonally adjusted form of the data. Because of changes in educational attainment classifications and population coverage, these data are available monthly only since 1992.

Relative unemployment rates are defined as the ratio of the unemployment rate of the unskilled group to the unemployment rate of the skilled group. Given that there are four levels of educational attainment, there are six relative unemployment rates. Summary statistics on these ratios are given in Table 1 for the full sample period: January 1992–December 2003.

Several facts emerge from Table 1. First, the mean of each ratio is greater than 1. In any group comparison, the relatively unskilled group has a higher unemployment rate on average. Second, the larger is the educational differential (when clearly distinguishable), the larger is the relative unemployment rate on average. Third, the ratio of the educational tails, Dropouts/College, is the most volatile.

II. Insights from Theory

The literature overviewed in the Introduction suggests that cyclical aggregate economic activity and technical adoption can have important direct effects on relative educational unemployment rates. The hypothesis of skill-biased technological change is consistent with an increase in relative unemployment as a result of an increase in the pace of technical adoption. The high-pressure-economy hypothesis, however, is consistent with a decrease in relative unemployment as the economy expands due possibly to the expansion of opportunities available to the relatively unskilled. Of course, there may be other factors influencing relative unemployment rates, but focusing on these two central factors, one can summarize the relevant intuitive content of these competing hypotheses with the following (linear) relation:

$$\text{(1)} \qquad \mathrm{RU}_t = \alpha_0 + \alpha_1 A_t + \alpha_2 C_t + z_t.$$

In equation (1), RU is the relative unemployment rate, A is the rate of technical adoption, C represents the (business) cycle, and z is a portmanteau variable for other influences on relative unemployment. Consistent with the intuitions just summarized, the signs of the slope coefficients are $\alpha_1 > 0$ and $\alpha_2 < 0$.

A significant literature (including several leading textbooks) allows real aggregate economic activity to be influenced by unanticipated monetary policy in the short run and by supply shocks. These factors are often thought to lead the cycle. Thus,

$$\text{(2)} \qquad C_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 S_{t-1} + e_t.$$

Here, P is a measure of monetary policy, S is a measure of supply shocks, and e is a portmanteau variable for other influences on cyclical economic activity. Of course, equation (2) is a (linear) simplification of a broad class of models. A nontrivial part of the intuitive content of those models, however, is encapsulated in the signs of β_1 and β_2. For an interest-rate-based measure of policy, an unanticipated relaxation of policy should spur economic activity. That is, $\beta_1 < 0$. An adverse supply shock (such as a positive oil price shock) should slow economic activity, $\beta_2 < 0$.

A final intuition draws on the literature that revived interest in the Schumpeterian process of creative destruction. Ricardo Caballero and Mohamad Hammour (1994), for example, present evidence that the rate of job creation is pro-cyclical even in the presence of adjustment costs. If experimentation with alternative business practices and new technologies is more likely to accompany the creation of jobs, then it may be reasonable to associate the job creation process with the pace of technical adoption, as Caballero and Hammour do. Therefore, technical adoption should be positively related to the level of real aggregate economic activity. Additionally, new technical ideas created in the past could be an important influence on the current pace of technical adoption. Symbolically, this intuition is represented as

$$A_t = \gamma_0 + \gamma_1 C_t + \gamma_2 T_{t-1} + w_t. \tag{3}$$

Here, T is a measure of the rate of creation of new technical ideas, and w is a portmanteau variable for other influences on the pace of technical adoption. The intuitive content of this class of models is consistent with $\gamma_1 > 0$. However, because the time it takes to sort through new technical possibilities could slow or even decrease the pace of actual adoption, $\gamma_2 \gtreqless 0$.

In the next section, I estimate a number of empirical models of relative educational unemployment. The challenge of interpreting the estimated models is eased by the insights summarized in this section. To see this, note that equations (1), (2), and (3) imply a relationship between relative educational unemployment, monetary policy, supply shocks, and technical ideas of the form:

$$\mathrm{RU}_t = \delta_0 + \delta_1 P_{t-1} + \delta_2 S_{t-1} + \delta_3 T_{t-1} + \nu_t \tag{4}$$

where, for example, $\delta_1 = \beta_1(\alpha_1\gamma_1 + \alpha_2)$, and ν is a linear combination of z, e, and w. Notice that the sign of the reduced-form coefficient δ_1 is indeterminate. Given that $\beta_1 < 0$, the sign of δ_1 depends on whether the negative influence on relative unemployment implied by the high-pressure-economy hypothesis outweighs the positive impact of technical adoption on relative unemployment. If the effects offset one another, then policy will not have any effect on relative unemployment. Although presented here in a highly stylized context, the competition between hypotheses to command the sign of δ_1 proves to be quite useful for interpreting the empirical results below.

Equation (4) has the structure of a distributed lag model. Of course, its lag structure is quite restrictive. One could easily imagine relaxing that restriction by including more lags on the policy, supply shock, and technical-ideas variables. Also, one might also want to include lags of the dependent variable. In the empirical work below, I in fact do this.[1]

III. Explaining Relative Unemployment: Evidence from ADL Models

A. *Specification*

Single-equation models conveniently provide answers to two empirical questions of interest. The first is: Do monetary policy surprises contain predictive power for relative unemployment controlling for supply shocks and technical ideas? The second is: What is the cumulative effect on relative unemployment of a policy surprise?

The structure of these models is motivated by the discussion in Section II. I consider autoregressive distributed lag (ADL) models of the following form:

$$\mathrm{RU}_t = \lambda_0 + \sum_{i=1}^{12} \lambda_i P_{t-i} + \sum_{i=1}^{12} \mu_i S_{t-i} + \sum_{i=1}^{12} \pi_i T_{t-i} + \sum_{i=1}^{12} \kappa_i \mathrm{RU}_{t-i} + \eta_t. \tag{5}$$

To see the connection between equations (4) and (5), consider the following reparameterization of (5):

[1] The relationship between monetary policy and unemployment differentials along other demographic lines (including race) is considered by Seth Carpenter and William Rodgers (2004).

$$\text{(6)}\quad \mathrm{RU}_t = \theta_0 + \theta^* P_{t-1} + \rho^* S_{t-1} + \phi^* T_{t-1} + \sum_{i=1}^{12} \theta_i \Delta P_{t-i} + \sum_{i=1}^{12} \rho_i \Delta S_{t-i} + \sum_{i=1}^{12} \phi_i \Delta T_{t-i} + \sum_{i=1}^{12} \kappa_i \mathrm{RU}_{t-i} + \xi_t$$

where, for example, $\theta^* = \sum_{j=1}^{12} \lambda_j$, $\theta_0 = \lambda_0$, and $\theta_i = -\sum_{j=i+1}^{12} \lambda_j$, $i = 1, 2, \ldots, 11$. Equation (6) looks a lot like equation (4). However, it permits a more generous lag structure. In the case of policy, for example, the reason for this is that it is known that it takes time for the effects of a monetary-policy initiative to work its way through the economy.[2] Any attempt to quantify the impact of monetary policy should allow for this.

B. *Measurement*

The measure of monetary policy that I employ is derived from the Federal Funds Futures market data from the Chicago Board of Trade (CBOT) and the monthly average effective Federal Fund rate reported by the Federal Reserve. The Federal Funds Futures market data are described in John Carlson et al. (1995). Federal Funds Futures contracts began trading on the CBOT in October 1988. The implied average Federal Funds rate for, say, the coming month can be easily derived from the settlement price of a contract on any day of the preceding month.

I follow Glenn Rudebusch (1998) in constructing one-step-ahead forecast errors as $r_t - E(r_t|\Omega_{t-1})$ where r is the Federal Funds rate and Ω represents the set of information available to agents at the given time period. The expectation, drawn from the futures market, is based on the settlement price of a futures contract on the last day of the preceding month. Negative forecast errors are associated with unanticipated interest-rate reductions. Conversely, positive forecast errors are associated with unanticipated interest-rate increases. Because of the Federal Reserve's ability to control the Federal Funds rate over the course of a month, I associate monetary policy surprises with the one-step-ahead forecast errors of the Federal Funds rate: $P_t \equiv r_t - E(r_t|\Omega_{t-1})$.

The measure of supply shocks, S_t, is James Hamilton's (2003) net oil price increase relative to a three-year horizon. Hamilton argues that upward oil price shocks have had a significant negative impact on overall economic activity in the United States in the post-World War II period. To fully capture the oil price–U.S. GDP relationship in the more recent period, Hamiltonian measures an oil price shock as the amount by which oil prices in month t exceed their peak value over the previous 36 months. If they do not exceed their previous peak, then the measure is taken to be zero.

The proxy for the rate at which new technical ideas are introduced, T_t, is the growth rate of real industrial research and development (R&D) expenditure. These data are drawn from the National Science Foundation (NSF) (2004). The NSF reports these data annually by performing sector and by source of funding. The raw annual data were converted to a monthly frequency via interpolation.

C. *Estimation and Testing*

Panel A of Table 2 reports the results of chi-square tests for predictive power from equation (5).[3] The null hypothesis for the chi-square tests is that all of the slope coefficients are zero. Focusing on the monetary-policy variable, the null hypothesis is rejected for three of the six measures of relative unemployment at conventional significance levels. Interestingly, when considered jointly, temporary monetary surprises matter most for relative unemployment rates involving those with a college degree or better.

[2] Two considerations influenced the choice of lag length. The first was the desire to allow time for the effect of the shock to be felt. The second was the desire to preserve degrees of freedom.

[3] The models in Table 2 include a post-March 2001 dummy variable. The reason for this and estimates of its coefficient are detailed in the next section.

TABLE 2—ESTIMATION AND TESTING RESULTS

A. *Predictive Power*

Dependent variable	Policy	Supply	Technical	Own lags
Dropouts/College	0.001	0.000	0.000	0.000
High School/College	0.000	0.000	0.000	0.000
Some College/College	0.000	0.194	0.000	0.000
Dropouts/Some College	0.198	0.000	0.000	0.000
High School/Some College	0.207	0.000	0.000	0.000
Dropouts/High School	0.344	0.000	0.000	0.000

B. *Cumulative Multiplier*

Dependent variable	Policy	Supply	Technical	$\bar{R}^2$
Dropouts/College	4.502*	0.004	0.093	0.812
	(0.369)	(0.196)	(0.186)	
High School/College	1.344*	−0.002	−0.066*	0.656
	(0.053)	(0.019)	(0.022)	
Some College/College	1.011*	−0.006	−0.177*	0.390
	(0.023)	(0.017)	(0.019)	
Dropouts/Some College	0.496*	0.016	0.289*	0.670
	(0.193)	(0.020)	(0.012)	
High School/Some College	0.873*	0.010	0.091*	0.321
	(0.049)	(0.020)	(0.019)	
Dropout/High School	−0.529*	0.000	0.139*	0.572
	(0.044)	(0.017)	(0.023)	

Notes: Each model includes a post-2001 dummy variable (reported in Table 3). Panel A reports p values associated with the null hypothesis that the coefficients are zero on lags 1–12 of the column variable. The test statistic is X^2, df = 12. Panel B reports cumulative multipliers, with standard errors in parentheses.

* Statistically significant at the 5-percent level.

The parameter

$$\Theta = \theta^* \bigg/ \left(1 - \sum_{i=1}^{12} \kappa_i\right)$$

derived from equation (6) holds the key to the answer of the second question: What is the cumulative effect on relative unemployment of a policy surprise? Often referred to as the cumulative multiplier, Θ measures the total effect on relative unemployment of a surprise one unit increase in policy.[4] Panel B of Table 2 reports estimates of the cumulative multiplier from equation (6). For five of six relative educational unemployment rates, Θ is positive and statistically significant. For the sixth measure it is negative and statistically significant. One interpretation of these findings is grounded in the intuition developed following equation (4).

As with δ_1, it would seem (intuitively) that $\Theta > 0$ is consistent with the high-pressure-economy hypothesis, while $\Theta < 0$ is consistent with the hypothesis that technical adoption hurts the relatively unskilled. If the two hypotheses offset one another, one would expect $\Theta = 0$ statistically. The results in Table 2 suggest that the high-pressure-economy hypothesis dominates over the sample period.

IV. Robustness and Qualifications

The previous quantitative results provided answers to two very specific questions. In this section, the robustness of those results is considered. I test for parameter stability.

A. *On the Interior*

A common perception is that significant structural change occurred in the U.S. macroeconomy during the boom of the late 1990s. Structural change that redistributes employment opportunities across educational groups may have altered the relationship between relative educational unemployment and its determinants over the business cycle. If economy-wide structural change did occur in the late 1990s, then it might be reasonable to think that it would induce shifts in the parameters of the empirical model.

To investigate this possibility, I calculate a sequence of Chow tests for each measure of relative unemployment over the interior of the sample (March 1996–October 1999) and the Andrews 5-percent critical value with 35-percent trimming and 49 restrictions (Donald W. K. Andrews, 1993). The null hypothesis of no break in all of the coefficients in the ADL models is rejected in only two of six cases: Dropouts/College and Dropouts/High School. The dates of these breaks are July 1999 and September 1997, respectively. Thus, there is some evidence that the dynamic multipliers were unstable during the late 1990s, but it is not overwhelming.

[4] In my application, this would amount to an unanticipated 1-percentage-point increase in the Federal Funds rate.

TABLE 3—ESTIMATES OF POST-MARCH 2001 DUMMY COEFFICIENT

Education level (dependent variable)	Coefficient
Dropouts/College	−0.573* (0.106)
High School/College	−0.245* (0.038)
Some College/College	−0.329* (0.061)
Dropouts/Some College	−0.165* (0.039)
High School/Some College	−0.041* (0.015)
Dropouts/High School	−0.079* (0.027)

Notes: Post-March 2001 dummy = 1 for $t \geq$ 2001:3. Estimates are for models in Table 2. Standard errors are reported in parentheses.

* Statistically significant at the 5-percent level.

B. *At the End*

Each model estimated in Table 2 includes a post-March 2001 dummy variable. This dummy, which allows only the constant to shift, is included in order to assess how much weight should be given to the possibility that structural change impacted the unconditional mean of relative unemployment. Erica Groshen and Simon Potter (2003), for example, present evidence that a substantial reallocation of jobs across industries occurred during the 2001 recession. They argue that these reallocations are permanent in nature and that they, along with a change in the use of temporary layoffs by employers, are important sources of sluggish labor-market performance in the recovery from the 2001 recession. If levels of educational attainment vary across industries, then a change in the composition of jobs across industries could influence the average level of relative educational unemployment.

Table 3 reports the estimated coefficient on the post-March 2001 dummy in the models of Table 2. In each model, the estimated coefficient is negative and statistically significant. Thus, the evidence suggests that, relatively speaking, the incidence of unemployment shifted (structurally) toward the better-educated during the 2001 recession and its immediate aftermath.

V. Conclusions

Six measures of relative educational unemployment (with unemployment of the less skilled in the numerator) are studied. For each ratio involving those with a college degree or better, the evidence from reduced-form dynamic models indicates that monetary-policy surprises, measured as the one-step-ahead forecast error of the Federal Funds rate derived from the Federal Funds Futures market, forecast relative unemployment controlling for supply shocks and new technical ideas. For five of six ratios, the cumulative multiplier measuring the effect of a monetary surprise on relative unemployment is positive and statistically significant. This evidence is consistent with the view that the advantages of tight labor markets outweigh the impact of technical adoption on relative unemployment over the business cycle.

The sensitivity of the results to structural change is considered also. The results of parameter stability tests indicate that the incidence of unemployment shifted toward the better-educated during the 2001 recession and its immediate aftermath.

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