MODELING UNEMPLOYMENT RATES BY RACE AND GENDER:

A NONLINEAR TIME SERIES APPROACH

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INTRODUCTION

The primary objectives of many macroeconomic policy makers are to promote economic growth and to reduce employment variability. The former objective relates to the level of the unemployment rate, with greater growth corresponding to a lower unemployment rate, and is often mentioned in conjunction with the degree of "tightness" in the labor market. *Ceteris paribus*, lower unemployment rates are preferred to higher unemployment rates (that is, in the absence of upward wage and price pressures). The second objective, promoting employment stability, relates to the variability of the unemployment rate, which can be taken as a measure of the labor market risk of obtaining successful employer-employee matches. A labor market that is characterized by a high degree of variability of the unemployment rate is generally less desirable than one with a lower degree of variability, because of the high degree of labor market risk.

Just as unusually high unemployment rates generally cause concern, it is typically the case that fluctuations in output and employment are also cause for concern when they become sufficiently large. This element of the labor market is a fundamental feature of a number of macroeconomic models that include a social welfare function and/or a loss function that depends on fluctuations in output and employment [Svensson, 1997; Dittmar, Gavin, and Kydland, 1999; Lucas, 2000]. Any economic policy geared towards reducing fluctuations in unemployment depends on a thorough understanding of how the unemployment rate responds to economic shocks.

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To comprehend fully the likely impact of an economic policy on the unemployment rate, it must be understood that the economy's aggregate unemployment rate is a weighted average of the unemployment rates of various demographic groups. There is no *a priori* reason to believe that the unemployment rate of each demographic group exhibits precisely the same time series behavior, or that it exhibits the same response to a given shock. An economic policy designed to reduce the aggregate unemployment rate, therefore, may reduce the unemployment rate of one demographic group by more than another demographic group and, over time, it may cause more variability in the unemployment rate of one demographic group than in the unemployment rate of another demographic group.

This paper presents an unemployment rate model that provides insight into how the time series behavior, in terms of both the mean and volatility, of the unemployment rates of black males, white males, black females, and white females differ. Specifically, the unemployment rate behavior of each demographic group is analyzed using a class of models capable of capturing nonlinearity in the variance of the unemployment rate series. The use of ARCH-class (autoregressive conditional heteroscedasticity) models has been shown to improve parameter estimates relative to an OLS model [Engle, 1982]. Further, techniques are employed in this study that allow each group's unemployment rate to respond asymmetrically to shocks in the mean of the (modeled) series, so that events associated with expansions and recessions may have different effects on the unemployment rate of different groups. A key issue examined in this study is whether or not the unemployment rate response to "good" news is the same as the response to "bad" news for each demographic group, where unanticipated shocks that lower the unemployment rate are considered to be "good" news and unanticipated shocks that increase the unemployment rate are considered to be "bad" news.

Our use of the terminology of "good" news/ "bad" news is in keeping with the usage in the literature on business cycle downturns/recessions. Movements associated with increases in real U.S. economic activity, such as higher employment or lower unemployment, are considered "good" news in the immediate sense [Anderson et al., 2003].

There are several possible reasons why the unemployment rate of different demographic groups may respond differently to an economic shock. Demographic differences in the unemployment rate response are likely to occur if certain demographic groups face discrimination or if different demographic groups have differing investments in human capital, for example. If a certain demographic group faces discrimination, members of that group would be less likely to be hired during an economic expansion, and more likely to be separated from their job during an economic contraction, than members of demographic groups that are not discriminated against. Likewise, if members of certain demographic groups have a lower investment in human capital, members of that group are less likely to be hired during an economic expansion, and more likely to be separated from their job during an economic contraction, than members of demographic groups that have a high level of human capital investment. In addition to human capital differences among the groups, there may be differences in other characteristics of the groups, such as differences in the age distribution or in the marital status distribution. If these differences affect a group's unemployment rate, there will tend to be differences in each group's unemployment rate response to an economic shock.

This paper develops and estimates a model to determine whether or not differences in unemployment rate volatility among demographic groups actually exist, utilizing an ARCH-class model. Although we recognize that the factors mentioned above are potential reasons for differences in unemployment rate volatility among different demographic groups, the purpose of the paper is not to determine the strength of the effect that each of the factors mentioned above has on the unemployment rate volatility of a particular group. As such, our model does not control for the human capital, marital status, age distribution, and other relevant characteristics of a particular demographic group that may affect its unemployment rate behavior.

LITERATURE REVIEW

Several studies have concentrated on understanding the behavior of unemployment rates disaggregated by race and gender. Bartlett and Haas [1997] contend that the natural rate of unemployment varies by demographic group. Fairlie and Sundstrom [1999] use over a century's worth of Census data to examine the unemployment rate gap between whites and blacks and find that reductions in the gap can be attributed to gains in education by blacks, while regional shifts in the economy, such as the migration of blacks from the rural South and relative decreases in demand for less-skilled workers, have increased the gap since 1970.

Hyclak and Stewart [1995] found that the unemployment rate of blacks was significantly more responsive to demand growth than the unemployment rate of whites. Their finding suggests that the unemployment rate fluctuations caused by economic shocks vary across demographic groups. Lynch and Hyclak [1984] also found differences in the time series behavior of unemployment rates across demographic groups. In particular, their results suggest that unemployment rates of blacks and males are more adversely affected by economic downturns than the unemployment rates of whites and females. In a related study, Ewing, Levernier, and Malik [2002], using generalized impulse response analysis, find that while real output growth reduces the unemployment rate of both blacks and whites and both males and females, the effect is larger and more persistent for blacks than for whites and for males than for females.

Prior research has focused on the forecasting and modeling of the aggregate unemployment rate when the unemployment rate is allowed to respond asymmetrically to the business cycle. Recognizing the asymmetric behavior of unemployment rates, a number of researchers have found evidence that suggests the aggregate unemployment rate exhibits nonlinearity. DeLong and Summers [1986] and Rothman [1991], for example, found the unemployment rate to increase quickly in economic downturns and to decline more slowly in expansions.

Recently, Rothman [1998] and Montgomery et al. [1998] compared the ability of nonlinear forecasting methods to that of more standard linear methods. Using quarterly U.S. unemployment rate data, Rothman [1998] conducted a comparison of various forecasting techniques and found that several nonlinear forecasting methods outperform conventional linear methods. These improvements in forecasting performance, however, are sensitive to whether or not the nonstationary unemployment rate series is transformed to a stationary series. In the transformed case, the nonlinear models generally outperform linear models, while the linear and nonlinear models perform similarly when the unemployment rate series is not transformed.

Montgomery et al. [1998] also presented a comparison of forecasting performance for several linear and nonlinear time series models of the U.S. unemployment rate. Their results suggest several important findings. First, incorporating monthly observations to forecast the quarterly unemployment rate generally improves forecasting performance when compared to using only quarterly data. Second, the unemployment rate does not appear to exhibit a consistent deterministic trend.[1] Third, significant improvements in the estimates of the coefficients obtained from standard linear models can be made using various nonlinear techniques.

Most prior studies that have examined the behavior of the unemployment rate have taken one of two approaches. The focus of the studies that account for nonlinearities in the behavior of the unemployment rate has been on the mean equation of the aggregate (national) unemployment rate, while most of those studies that examine differences in unemployment rates across demographic groups have used linear estimation methods. Our study combines these two approaches by modeling the unemployment rate of various demographic groups while allowing the variance of the series to vary over time. Our research, therefore, explicitly examines the conditional volatility of several disaggregated unemployment rates in order to understand more about how these rates behave and to obtain information on unemployment rate behavior that may be relevant to the construction of stabilization policy.

This study extends the existing literature by using a nonlinear time-series econometric technique to study differential effects of unanticipated shocks on unemployment rates of various demographic groups.[2] Clearly, economic policy geared towards affecting the aggregate unemployment rate could have vastly different effects on the unemployment situations of various demographic groups. If so, a better understanding of how the unemployment rates of black females, white females, black males, and white males respond to an economic shock is desirable.

DATA AND METODOLOGY

This paper seeks to model simultaneously both the mean and variance of the unemployment rates of various demographic groups. The data consist of the aggregate U.S. unemployment rate (u) and the unemployment rates of black males (u^{BM}), white males (u^{WM}), black females (u^{BF}), and white females (u^{WF}). Monthly observations of seasonally adjusted unemployment rates are obtained from the U.S. Bureau of Labor Statistics, *Employment and Earnings* (various issues) for the period of January 1972 through December 1999.

Table 1 presents descriptive statistics for each of the variables, both in levels and in first-differences. From Panel A, we see that the mean unemployment rate is higher for blacks than for whites and is higher for white females than white males. The medians follow a similar pattern, while the standard deviation is higher for blacks than for whites and is higher for males than for females. Panel B reveals that the absolute value of the mean change in unemployment rates for blacks is higher than it is for whites and is higher for females than for males. The standard deviation of the first-difference of unemployment rates is higher for blacks than for whites, for both males and female, while the medians are zero for all groups except black males.

TABLE 1
Descriptive Statistics

	Panel A: Unemployment rates in levels				
	u	u^{BF}	u^{BM}	u^{WF}	u^{WM}
mean	5.6086	10.9345	10.9066	5.1217	4.8012
median	5.4000	10.9000	10.6000	5.0000	4.5500
max	9.8000	18.2000	20.7000	8.3000	9.0000
min	3.4000	6.1000	5.2000	3.0000	2.7000
std. dev.	1.3130	2.3006	3.0485	1.1344	1.3302
skewness	0.7006	0.4787	0.6599	0.5104	0.7892
kurtosis	3.3369	3.0982	3.5276	2.7630	3.4618
	Panel B: Unemployment rates in first-differences				
	Δu	Δu^{BF}	Δu^{BM}	Δu^{WF}	Δu^{WM}
mean	–0.0039	–0.0078	–0.0033	–0.0057	–0.0033
median	0.0000	0.0000	–0.1000	0.0000	0.0000
max	0.8000	2.1000	1.9000	1.1000	0.7000
min	–0.5000	–1.5000	–1.7000	–0.8000	–0.6000
std. dev.	0.1729	0.5934	0.6359	0.2109	0.2024
skewness	0.7804	0.0535	0.1968	0.5521	0.3983
kurtosis	5.2131	3.3856	3.0009	6.5748	3.8252

Note: The number of observations in Panels A and B are 336 and 335, respectively. The sample period is January 1972-December 1999.

The standard deviation of the unemployment rate of males being larger than that of females is a somewhat surprising finding. Since females tend to be the primary homemaker/caregiver in many households, females can be thought of as being secondary workers to a greater extent than males. As such, our *a priori* expectation is that the unemployment rate of females will have a larger standard deviation than the unemployment rate of males. One possible reason for our contradictory finding is that females may be disproportionately employed in sectors that are less cyclical than the sectors in which males are disproportionately employed. Females may be disproportionately employed in certain service sectors, for example, while males may be disproportionately employed in construction and manufacturing. A second possible reason may be related to differences in the labor force participation behavior of females compared to males. If unemployed females are more likely to exit the labor force during an economic contraction than unemployed males, then the official unemployment rate of females will be less adversely affected by a contraction than the official unemployment rate of males. As such, the unemployment rate of females will tend to be more stable (that is, have a lower standard deviation) during an economic contraction than the unemployment rate of males.

For the unemployment rate level data (Panel A in Table 1), the ANOVA F-statistic equals 903.04 (with an associated p-value = 0.00) for the equality of the means of the levels of unemployment rates for the gender/race groups. The χ^2 statistic for testing the equality of medians of the gender/race unemployment rate levels equals 985.92 (with p-value = 0.00). The Brown-Forsythe (modified Levene) test for the equality of variances of the gender/race unemployment rate levels is F = 92.94 (with p-value = 0.00).

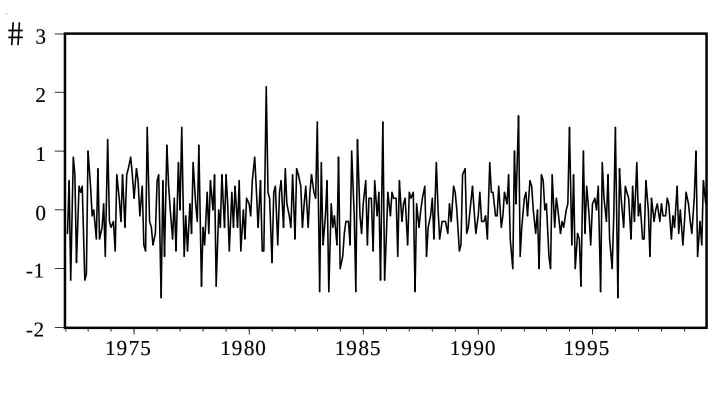
Thus, we reject the hypothesis that the mean monthly unemployment rate is equal across the four demographic groups.[3] We also reject the hypotheses that the median of the monthly unemployment rate and the standard deviation of the monthly unemployment rate are equal across the four groups.[4]

For the unemployment rate in first-difference data (Panel B in Table 1), we also conduct tests regarding differences in the mean, median, and standard deviation of the four groups. The ANOVA F-statistic equals 0.01 (with p-value = 0.99) for testing the equality of means of the first-differences of the gender/race unemployment rates. The χ^2 statistic for testing the equality of medians of the first-differences of the gender/race unemployment rates equals 8.97 (with p-value = 0.03). The Brown-Forsythe test for the equality of variances of the gender/race unemployment rates is F = 146.27 (with p-value = 0.00). Thus, we do not reject the hypothesis that the mean of the first-differences of monthly unemployment rates are equal across demographic groups. We do, however, reject the hypotheses that the median of the first-difference of monthly unemployment rate and the standard deviation of the first-difference of monthly unemployment rate are equal across the four groups.[5]

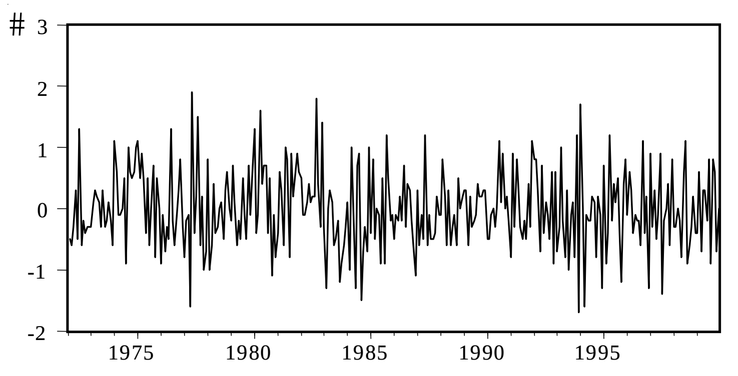
It is also worth noting that, with the possible exception of u^{BM}, the first-difference of each series exhibits excess kurtosis (fat tails). The ARCH-class models are thus especially appealing as they are well suited to modeling this feature [Harvey, 1994]. Figure 1 presents plots of the month-to-month changes in the unemployment rates of each of the demographic groups. Note that, consistent with there being autoregressive conditional heteroscedasticity, there appears to be periods of volatility clustering, which suggests that the variance of the series varies over time in a way that depends on how large the variance was in the past (several) period(s).

FIGURE 1
Changes in Unemployment Rates by Race and Gender
(January 1972–December 1999)

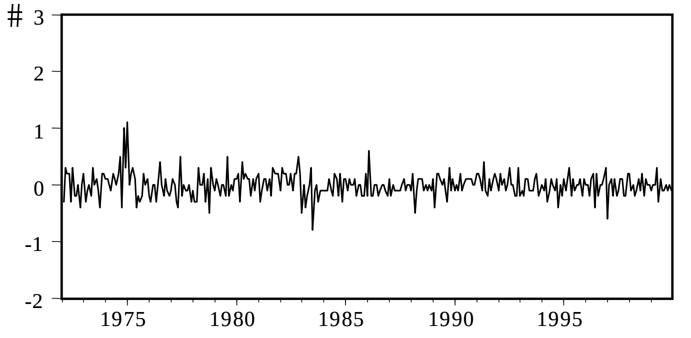
Panel A: Δu^{BF}



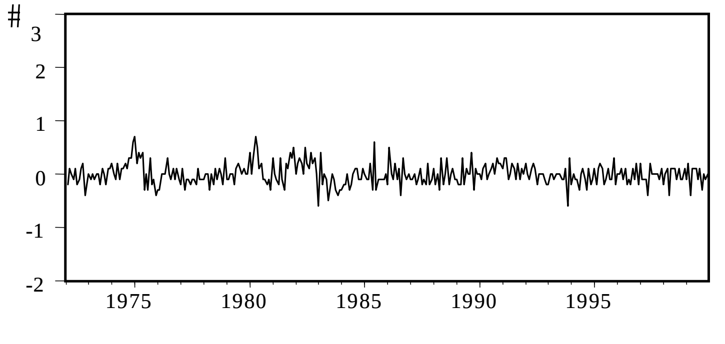
Panel B: Δu^{BM}



Panel C: Δu^{WF}



Panel D: Δu^{WM}



Engle [1982] and Bollerslev [1986] have shown that in the presence of ARCH effects, modeling both the mean and the variance of the process under investigation improves the efficiency of the parameter estimates. In the ARCH-class of models, the variance of the series depends on past volatilities, often going back several periods, with older shocks having less of an effect on current volatility than more current shocks.[6] In fact, the effect of an unemployment rate innovation on current volatility will decline geometrically over time.

The initial step in the analysis is to construct a simple autoregressive (AR) model of the mean change in the unemployment rate of each of the demographic groups. The conventional (linear) model assumes that the variance of the error process is constant (that is, the unconditional variance and the conditional variance exist, are greater than zero, and the current volatility is independent of past volatilities). We follow the standard unemployment rate forecasting framework outlined in Payne, Ewing, and George [1999], in which the univariate AR model is augmented with the immediate past change(s) in the aggregate U.S. unemployment rate. They provide evidence that it is appropriate to specify the model in first-differences when constructing forecasting models for disaggregated unemployment rates that include the aggregate unemployment rate as an explanatory variable.[7]

To illustrate the generalized-ARCH or GARCH(p,q) model, consider the following set of equations, which are simultaneously estimated via the method of maximum likelihood.[8]

$$\Delta u_t^{ij} = \beta_0 + \sum\nolimits_{k=1}^{m} \beta_k \Delta u_{t-k}^{ij} + \sum\nolimits_{l=1}^{n} \delta_l \Delta u_{t-l} + \varepsilon_t, \tag{1}$$

$$h_t^2 = \alpha_0 + \sum\nolimits_{a=1}^{q} \alpha_a \varepsilon_{t-a}^2 + \sum\nolimits_{b=1}^{p} \phi_b h_{t-b}^2, \tag{2}$$

where $\varepsilon_t \sim N(0,\ h_t^2)$ and ij denotes demographic group (BF, BM, WF, or WM). The mean equation, which includes m autoregressive lags and n lags of the change in the aggregate unemployment rate, is given by Equation (1), while Equation (2) is the (conditional) variance equation.[9] $V(\varepsilon_t \mid \Omega_{t-1}) = h_t^2$ is the conditional variance of ε_t with respect to the information set Ω_{t-1}. Equation (2) contains both a moving average component that may contain q lags and an autoregressive component that may contain p lags. An ARCH(q) model does not contain the autoregressive component in Equation (2).

The first step in the procedure is to find the best-fitting specification of Equation (1) using standard Box-Jenkins techniques and then test the chosen specifications for the existence of autoregressive conditional heteroscedasticity. The idea behind the Box-Jenkins technique is to find the "best-fitting" (in the sense of producing white noise residuals) and, preferably, parsimonious model. To this end, we examined the autocorrelation functions and Akaike's information criterion.[10] An AR(1) with one lag of the change in the aggregate unemployment rate was chosen for the black female, white female, and black male equations, while an AR(2) augmented with one lag of the change in the aggregate unemployment rate was chosen for the white male equation. The test described in Engle [1982, 1000] was used to test for the presence of ARCH effects. The mean equations all exhibited evidence of autoregressive conditional heteroscedasticity.[11] Estimation of ARCH-class models is therefore appropriate. The specification of the variance equation is determined in a manner similar to that of the mean equation (based on goodness-of-fit).

The results of the (G)ARCH models are presented in Table 2. In each case, the estimated values of the coefficient β_1 are negative and significant, indicating that the change in the unemployment rate from the previous month to the current month for all four demographic groups is negatively related to the previous period's change in the group's unemployment rate.[12] The estimated values of the coefficient δ_1 are positive and significant for all four demographic groups, indicating that the change in the unemployment rate from the previous month to the current month for all four demographic groups is positively related to the previous period's change in the national (aggregate) unemployment rate. The results indicate that the unemployment rate change of black males is more strongly affected by a change in the national unemployment rate than those of the other demographic groups. The unemployment rate change of white males is least affected (although the effect is still statistically significant at the .01 level) by a change in the national unemployment rate. The effect of a change in the aggregate (national) unemployment rate on the change in the unemployment rate of black males is more than twice as large as the effect on the change in the unemployment rate of white males. Also, note that in every case the autoregressive term or the moving average term, or both, from Equation (2) is significant.[13] These results suggest that the volatility of the unemployment rate change for black females, black males, white females, and white males is predictable. In each case, the unconditional variance of ε_t, given by $[\alpha_0 / (1 - \alpha_1 - \phi_1)]$, is constant and greater than zero as required. In fact, we find considerable differences in the magnitude of unconditional (long-run) variances between blacks and whites. The unconditional variances are found to be .3158 for black females, .3775 for black males, .0384 for white females, and .0367 for white males. Furthermore, the necessary condition for Equation (1) to be covariance stationary, $(\alpha_1 + \phi_1) < 1$, is satisfied in each case.[14]

TABLE 2
GARCH Estimation Results

	Δu^{BF}	Δu^{BM}	Δu^{WF}	Δu^{WM}
β_0	–0.0129	0.0045	–0.0121	–0.0082
	(0.6646)	(0.8943)	(0.2071)	(0.4205)
β_1	–0.3320	–0.2573	–0.3918	–0.1899
	(0.0000)	(0.0000)	(0.0000)	(0.0302)
β_2				0.1958
				(0.0001)
δ_1	0.4652	0.7292	0.4147	0.3059
	(0.0077)	(0.0007)	(0.0000)	(0.0018)
α_0	0.2629	0.0721	0.0134	0.0036
	(0.0000)	(0.3609)	(0.0081)	(0.3515)
α_1	0.1676	0.0540	0.2779	0.0575
	(0.0185)	(0.3081)	(0.0018)	(0.1929)
ϕ_1		0.7550	0.3728	0.8445
		(0.0013)	(0.0168)	(0.0000)

Note: Actual probability value in parentheses.

The results from estimating Equations (1) and (2) provide information as to how the conditional volatility of the unemployment rate changes responds to shocks or, in the language of the conditional volatility literature, to economic news. In particular, a shock to the unemployment rate of any group raises the volatility of that group's unemployment rate change. The sum $(\alpha_1 + \phi_1)$ provides information as to the degree of variance persistence. We find that unanticipated changes in a group's unemployment rate generate a greater degree of persistence in conditional volatility for males than for females, and for whites than for blacks. Ewing and Kruse [2002] use the conditional volatility of the unemployment rate as a measure of labor market risk. If less risk is preferred to more risk, *ceteris paribus*, then a lower degree of variance persistence is preferred to a higher degree of variance persistence. They suggest that a policy aimed at lowering conditional volatility and associate persistence, in general, is welfare enhancing, all else equal.

One useful and appealing feature of the GARCH model is that it allows one to compute j-period-ahead forecasts of volatility. This j-period-ahead forecast is given by $E_t[h^2_{t+j}] = (\alpha_1 + \phi_1)^j \{(h^2_{t+j}) - [\alpha_0/(1 - \alpha_1 - \phi_1)]\} + [\alpha_0/(1 - \alpha_1 - \phi_1)]$. As noted by Campbell, Lo, and MacKinley [1997], however, the forecasts of future variance in the conventional GARCH model are linear in current and past variances, which means that the GARCH model treats the impact of shocks as symmetric. Consequently, positive and negative economic shocks have the same effect on conditional volatility in the GARCH model.

In reality, it is possible for shocks to have asymmetric impacts such that the effect on volatility from a positive shock may be different from that from a negative shock. An ARCH-class model capable of detecting whether or not positive and negative shocks have symmetric impacts on volatility is the threshold (G)ARCH model or TARCH [Rabemananjara and Zakoian, 1993; Zakoian, 1994]. The ability to capture this behavior empirically in our examination of unemployment rate changes is especially desirable as these asymmetric effects have important implications regarding our understanding of economic stabilization.

We apply the TARCH model estimation technique to the gender/race unemployment rate changes to examine whether or not good news for the labor market (that is, a negative shock that lowers the unemployment rate below what was expected) has a greater impact on the volatility of the unemployment rate change than does bad news (that is, a positive shock that raises the unemployment rate above what was expected) for a particular demographic group. In other words, does the volatility of the unemployment rate change of a particular demographic group respond at the same speed and magnitude to “good” economic news as it does to “bad” economic news?

To understand the TARCH model and the impact of economic “news”, consider the following. Denote the series under investigation by x_t. Define $m_t \equiv E(x_t \mid \Omega_{t-1})$, where Ω represents the agent’s information set. In the language of Engle and Ng [1993], economic news is given by $\varepsilon_t \equiv x_t - m_t$. For the case in which x is the unemployment rate change, we can consider $\varepsilon_t > 0$ as “bad” news (indicative of recession) and $\varepsilon_t < 0$ as “good” news (indicative of expansion).

The TARCH model is capable of discerning differences between the impact that positive shocks and negative shocks have on the volatility of changes in the unemployment rate. The TARCH model is given by the following set of equations:

$$\Delta u_t^{ij} = \beta_0 + \sum_{k=1}^{m} \beta_k \Delta u_{t-k}^{ij} + \sum_{l=1}^{n} \delta_l \Delta u_{t-l} + \varepsilon_t , \tag{3}$$

$$h_t^2 = \omega + \rho \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \eta h_{t-1}^2 . \tag{4}$$

The specification for the conditional variance of the TARCH model is given by Equation (3), where $d_t = 1$ if $\varepsilon_t < 0$ and $d_t = 0$ otherwise.[15] Equation (3) allows positive and negative innovations to have differential effects on the conditional variance. A positive shock ($\varepsilon_t > 0$) has an impact of ρ, while a negative shock ($\varepsilon_t < 0$) has an impact of $\rho + \gamma$. If $\gamma = 0$, then the "news" is symmetric; if $\gamma \neq 0$, then the "news" is asymmetric. As in the (symmetric) GARCH case, the coefficient on the autoregressive term (η) reveals information as to the degree of volatility persistence.

The results from the estimation of the TARCH models are presented in Table 3. To determine if an asymmetric impact exists, one looks at the estimate of the γ coefficient to test statistically whether or not it is significantly different from zero. The γ coefficient is not statistically different from zero in the case of black females, black males, and white females, but is negative and statistically significant for white males. In the case of white males, therefore, the results suggest that the impact of negative innovations (good labor market news) differs from the impact of positive innovations (bad labor market news). In particular, given the negative sign on the γ coefficient for white males, it appears that good news ($\varepsilon_t < 0$) has a smaller impact on conditional volatility than bad news ($\varepsilon_t > 0$), for similar size unanticipated shocks.[16] One possible explanation for this finding is that the labor market for white males is more stable than that of the other groups, particularly in an economic growth period. This result is thus consistent with the argument that differences in demographic characteristics and human capital may explain some of the labor market advantage typically attributed to white males.

TABLE 3
TARCH Estimation Results

	Δu^{BF}	Δu^{BM}	Δu^{WF}	Δu^{WM}
β_0	–0.0161	–0.0026	–0.0073	–0.0059
	(0.5888)	(0.9368)	(0.4550)	(0.5519)
β_1	–0.3298	–0.2469	–0.3978	–0.2148
	(0.0000)	(0.0000)	(0.0000)	(0.0131)
β_2				0.1836
				(0.0001)
δ_1	0.4701	0.7687	0.4137	0.3062
	(0.0075)	(0.0003)	(0.0000)	(0.0006)
ω	0.2640	0.0690	0.0132	0.0024
	(0.0000)	(0.3562)	(0.0125)	(0.0473)
ρ	0.1192	0.0154	0.3568	0.0819
	(0.0482)	(0.7101)	(0.0106)	(0.0917)
γ	0.0898	0.0837	–0.2285	–0.1113
	(0.4928)	(0.3189)	(0.1082)	(0.0307)
η		0.7633	0.4057	0.9046
		(0.0004)	(0.0140)	(0.0000)

Note: Actual probability value in parentheses.

SUMMARY AND CONCLUDING REMARKS

This paper modeled the monthly unemployment rate changes of black females, black males, white females, and white males over the 1972-99 period by simultaneously estimating both the mean and variance of each group. We found that shocks to a group's unemployment rate increased the (conditional) volatility of changes in that group's unemployment rate and that these effects persisted more for males than for females, and more for whites than for blacks.[17] Our results about the volatility of gender/race unemployment rate changes partially complement the earlier findings of Lynch and Hylcak [1984] and Ewing, Levernier, and Malik [2002], who determined that downturns in economic growth more adversely affected the (mean) unemployment rates of blacks than of whites, and more adversely affected the (mean) unemployment rates of males than of females. Our findings, in both the GARCH and TARCH models, indicate that, for both males and females, the change in the unemployment rate of blacks in response to a change in the aggregate (national) unemployment rate is larger than the change in the unemployment rate of whites in response to a change in the aggregate unemployment rate. Our results do not reveal a clear pattern regarding the response of a change in the unemployment rate of males relative to females, however, as the response of the black male unemployment rate change is larger than the black female unemployment rate change, and the response of the white male unemployment rate change is smaller than the white female unemployment rate change.

We also examined whether or not the impact of an innovation on the conditional variance for a particular demographic group was symmetric or asymmetric. The findings from the TARCH models suggested that the conditional variance is symmetric for white females, black females, and black males, but is asymmetric for white males. In particular, the findings indicate that innovations increase the conditional volatility changes in each group's unemployment rate and have symmetric effects for all groups except white males. Unanticipated declines ("good" news) in the unemployment rate of white males are associated with significantly lower increases in conditional volatility than are unanticipated increases ("bad" news) in the unemployment rate. For white males, therefore, good news is *really* good news as it corresponds not only to a lower unemployment rate but also to relatively less volatility in changes in the unemployment rate (as compared to the volatility experienced as a result of an unexpected increase in the unemployment rate of similar magnitude).

The findings of the paper bring attention to the effects of economic shocks, defined as those unexpected events that raise or lower unemployment rates, on the volatility of unemployment rate changes. Furthermore, our study reinforces the contention of Bartlett and Haas [1997] that economic policy that focuses on the aggregate unemployment rate may have different effects on the unemployment situations of various groups. Our findings imply that fiscal and/or monetary policies that are geared towards changing the aggregate unemployment rate may lead one demographic group to experience more or less employment volatility than another.

NOTES

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1. This is consistent with the finding of Payne, Ewing, and George [1999].
2. Related research has focused on the underlying reasons for racial/gender differences in unemployment rates. These studies have looked at differences in job displacement, reservation wages, job mobility, and job search by race/gender. See Fairlie and Kletzer [1998], Petterson [1998], and Keith and McWilliams [1995; 1999].
3. In a series of pair-wise comparisons, we found that the mean monthly unemployment rate of white females is significantly higher (at the .01 level) than that of white males, the mean monthly unemployment rate of black males is significantly higher (at the .01 level) than that of white males, and the mean monthly unemployment rate of black females is significantly higher (at the .01 level) than that of white females. The mean monthly unemployment rate of black females is not statistically different from that of black males at even the .10 level of significance.
4. In a series of pair-wise comparisons, we found that the standard deviation of the monthly unemployment rate of white males is significantly higher (at the .01 level) than that of white females, the standard deviation of the monthly unemployment rate of black males is significantly higher (at the .01 level) than that of white males, the standard deviation of the monthly unemployment rate of black males is significantly higher (at the .01 level) than that of black females, and the standard deviation of the monthly unemployment rate of black females is significantly higher (at the .01 level) than that of white females.
5. These preliminary tests, for both the levels and first-differences of the series, serve simply to highlight the potential differences that may exist among unemployment rates disaggregated by race and gender. Of course, the presence of serial correlation might bias the results of the hypothesis tests. As such, a more formal examination of the data is warranted. In particular, in the time-series models described below, serial correlation is explicitly taken into account.
6. Bollerslev [1986] introduced the generalized autoregressive conditional heteroskedasticity (GARCH) model, which is more parsimonious than an ARCH(q) model when q is of a high order.
7. This assumes that in order to induce stationarity of the series that it suffices to difference the unemployment rate levels. Results from augmented Dickey-Fuller tests suggested that each of the unemployment rates were first-difference stationary. These findings are consistent with the treatment of the unemployment rates in Montgomery et al. [1998] and Payne, Ewing, and George [1999]. Results of the ADF tests are available upon request. Perron [1989] notes, however, that in the presence of a known structural break, a researcher using the standard ADF test may incorrectly conclude the series has a unit root. Experimentation with the Perron procedure for testing for unit roots in the presence of structural breaks did not alter our finding that we could not reject the null of nonstationarity in the level of the gender-race unemployment rates. Additionally, we conducted the nonparametric unit root test developed by Cochrane [1988]. The Cochrane variance ratio statistic and corresponding Z statistics (in parentheses) for white males, white females, black males, and black females were 0.88 (–0.19), 0.36 (–1.02), 0.58 (–0.67), and 0.35 (–1.03), respectively. In no case do we reject the null hypothesis of a unit root. By itself, the finding of nonstationarity implies that unemployment rates by race and gender do not return to an equilibrium value following shocks. Some may take this as evidence in support of a real business cycle model; however, if the natural rate is actually time varying (in mean), then it may be that there exists a stationary linear combination of the group's rate and the natural rate. In this case, one could not reject the standard, Keynesian view of the business cycle.
8. Enders [1995] describes how the method of maximum likelihood can be applied to GARCH estimation. Greene [1997] also has a good summary of the GARCH model and the maximum likelihood estimation procedure.
9. We computed the quasi-maximum likelihood covariances and standard errors as described in Bollerslev and Wooldridge [1992]. The models are estimated under the assumption that the errors are conditionally normally distributed.
10. See Enders [1995] and Mills [1999] for more information on the use of Box-Jenkins techniques and selection criteria for specifying time series models.

11. The test statistic is distributed as a χ^2 with degrees of freedom equal to the number of restrictions. Specifically, we found first-order ARCH effects for black females, white females, and white males with corresponding estimated test statistics of 3.47 (p-value = .06), 5.17 (p-value = .02), and 5.06 (p-value = .02). Evidence of third-order ARCH effects was found for black males with a test statistic of 8.39 (p-value = .03). These findings suggest that past values of volatility can be used to predict current volatility.
12. The necessary and sufficient condition for an AR(1) process to be stationary is that $|\beta_1| < 1$ and is satisfied in the case of black males, black females, and white females. The necessary and sufficient conditions for an AR(2) process to be stationary are that $\beta_1 + \beta_2 < 1$, $\beta_2 - \beta_1 < 1$, and $|\beta_2| < 1$ and are satisfied in the case of white males.
13. For black males, white females, and white males, we conducted tests of the joint null hypothesis that $\alpha_1 = \phi = 0$ and were able to reject the null hypothesis in each case.
14. Q-statistics suggested that the mean equations were free from serial correlation. Correlograms of the squared standardized residuals indicated that the variance equations were correctly specified with no evidence of remaining ARCH effects. Jarque-Bera tests indicated that the standardized residuals may not be normally distributed. The estimates are still consistent, however, under quasi-maximum likelihood assumptions (see Bollerslev and Wooldridge [1992]).
15. We assume normally distributed errors.
16. As in the GARCH case, we find that the unconditional variance exists and is a mean-reverting process.
17. The findings of persistent volatility following a shock are not inconsistent with an expectations-augmented Phillips curve. See Ewing and Seyfried [2000].

REFERENCES

Anderson, T. G., Bollerslev, T., Diebold, F. X., and Vega, C. Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange. *American Economic Review*, March 2003, 38-62.

Bartlett, R. L. and Haas, P. The Natural Rate of Unemployment by Race, Gender, and Class. *Challenge*, November/December 1997, 85-98.

Bollerslev, T. Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, April 1986, 307-27.

Bollerslev, T. and Wooldridge, J. Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances. *Econometric Reviews*, August 1992, 143-72.

Campbell, J. Y., Lo, A. W., and MacKinley, A. C. *The Econometrics of Financial Markets*. Princeton, N.J.: Princeton University Press, 1997.

Cochrane, J. How Big is the Random Walk in GNP? *Journal of Political Economy*, October 1988, 893-920.

DeLong, J. B. and Summers, L. Are Business Cycles Symmetrical? In *The American Business Cycle, Continuity and Changes*, edited by. R. J. Gordon. Chicago: University of Chicago Press and NBER, 1986

Dittmar, R., Gavin, W. T., and Kydland, F. E.. The Inflation-Output Tradeoff and Price-Level Targets. *Federal Reserve Bank of St. Louis Review*, January/February 1999, 23-31.

Enders, W. *Applied Econometric Time Series*. New York: John Wiley & Sons, 1995.

Engle, R. Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of the United Kingdom Inflation. *Econometrica*, July 1982, 987-1008.

Engle, R. and Ng, V. K. Measuring and Testing the Impact of News on Volatility. *Journal of Finance*, December 1993, 1749-78.

Ewing, B. T. and Kruse, J. B. The Impact of Project Impact on the Wilmington, NC Labor Market. *Public Finance Review*, July 2002, 296-309.

Ewing, B. T. and Seyfried, W. L. Some Additional Thoughts about the Phillips Curve. *Social Science Quarterly*, June 2000, 680-82.

Ewing, B. T., Levernier, W., and Malik, F. The Differential Effects of Output Shocks on Unemployment Rates by Race and Gender. *Southern Economic Journal*, January 2002, 584-99.

Fairlie, R. B. and Kletzer, L. G. Jobs Lost, Jobs Regained: An Analysis of Black/White Differences in Job Displacement in the 1980s. *Industrial Relations*, October 1998, 461-75.

Fairlie, R. B. and Sundstrom, W. A. The Emergence, Persistence, and Recent Widening of the Racial Unemployment Gap. *Industrial and Labor Relations Review*, January 1999, 252-70.

Greene, W. H. *Econometric Analysis*. Upper Saddle River, N.J.: Prentice-Hall, Inc., 1997.

Harvey, A. C. *Time Series Models*. Cambridge, Mass.: MIT Press, 1994.

Hyclak, T. and Stewart, J. B. Racial Differences in the Unemployment Response to Structural Changes in Local Labor Markets. *Review of Black Political Economy*, Spring 1995, 29-42.

Keith, K. and McWilliams, A. The Wage Effects of Cumulative Job Mobility. *Industrial and Labor Relations Review*, October 1995, 121-37.

__________. The Returns to Mobility and Job Search by Gender. *Industrial and Labor Relations Review*, April 1999, 460-77.

Lucas, R. Inflation and Welfare. *Econometrica*, March 2000, 247-274.

Lynch, G. J. and Hyclak, T. Cyclical and Noncyclical Unemployment Differences among Demographic Groups. *Growth and Change*, January 1984, 9-17.

Mills, T. C. *The Econometric Modeling of Financial Time Series*. Cambridge, U.K.: Cambridge University Press, 1999.

Montgomery, A. L., Zarnowitz, V., Tsay, R. S., and Tiao, G. C. Forecasting the U.S. Unemployment Rate. *Journal of the American Statistical Association*, June 1998, 478-93.

Payne, J. E., Ewing, B. T., and George, E. Time Series Dynamics of U.S. State Unemployment Rates. *Applied Economics*, November 1999, 1503-10.

Perron, P. The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis. *Econometrica*, November 1989, 1361-1401.

Petterson, S. M. Black-White Differences in Reservation Wages and Joblessness: A Replication: Comment. *Journal of Human Resources*, Summer 1998, 758-70.

Rabemananjara, R. and Zakoian, J. M. Threshold ARCH Models and Asymmetries in Volatility. *Journal of Applied Econometrics*, January-March 1993, 31-49.

Rothman, P. Further Evidence on the Asymmetric Behavior of Unemployment Rates over the Business Cycle. *Journal of Macroeconomics*, Spring 1991, 291-98.

__________. Forecasting Asymmetric Unemployment Rates. *Review of Economics and Statistics*, February 1998, 164-68.

Svensson, L. E. O. Optimal Inflation Targets, “Conservative” Central Banks, and Linear Inflation Contracts. *American Economic Review*, March 1997, 98-114.

Zakoian, J. M. Threshold Heteroskedastic Models. *Journal of Economic Dynamics and Control*, September 1994, 931-55.