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Abstract

I examine whether the cyclical behavior of unemployment has changed over the post WWII period. Specifically, I test whether cyclical movements in unemployment have become more persistent. Finding that they have, indeed, become more persistent, I then take some initial steps in explaining why. I find that the increase in persistence has affected private nonfarm payroll employment as well as unemployment and that increased persistence appears to be widespread across industries. At the same time, increased persistence owes primarily to greater persistence in job finding rates and greater persistence in unemployment among permanent job losers. This combination suggests that the welfare loss from cyclical increases in unemployment is becoming increasingly concentrated among permanent job losers who become unemployed for extended durations during cyclical downturns.

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Have Cyclical Movements in the Unemployment Rate Become More Persistent?

I examine whether the cyclical behavior of unemployment has changed over the post WWII period. Specifically, I test whether cyclical movements in unemployment have become more persistent. Finding that they have, indeed, become more persistent, I then take some initial steps in explaining why. I find that the increase in persistence has affected private nonfarm payroll employment as well as unemployment and that increased persistence appears to be widespread across industries. The broad-based character of the break in persistence suggests that it is not the result of a change in one sector of the economy, but, instead, likely reflects changes to the economic shocks or propagation of these shocks that affect a wide spectrum of economic activity. At the same time, increased persistence owes primarily to greater persistence in job finding rates and greater persistence in unemployment among permanent job losers.[1] This combination suggests that the welfare loss from cyclical increases in unemployment is becoming increasingly concentrated among permanent job losers who become unemployed for extended durations during cyclical downturns.

I focus on the persistence of cyclical unemployment rather than volatility because numerous studies have already documented a decline in output volatility beginning in the early to mid 1980s and lasting until the recent recession, see McConnell and Perez-Quiros (2000) among others. In contrast, examinations of the persistence in economic activity have been relatively rare. One example is Nalewaik (2007), who finds that the apparent mid-1980s break in the volatility of economic activity appeared to be

[1] Here and throughout the text, I use the term "permanent job losers" to refer to individuals who become unemployed after losing their job and who report not expecting to be recalled to their former job. In other words, I use this term as shorthand for workers whose *previous job* appears to have been lost "permanently", not for workers who expect to be unemployed permanently.

accompanied by an increase in the persistence of periods of below-trend economic growth, a finding consistent with the results presented in this paper. In addition, while recent events suggest that the decline in economic volatility has ended, recent readings in the labor market suggest that a period of greater persistence in unemployment is likely continuing to affect the behavior of the macro economy.[2]

After showing that unemployment has become more persistent, I next use more disaggregated data to examine why. I first show that the increase in unemployment persistence is mirrored by an increase in employment persistence. This allows me to use the large sample size of the BLS' Current Employment Statistics (CES) survey, or establishment survey, to investigate changes in persistence by industry. I find that increasing persistence is widespread across industries, suggesting that the cause of greater unemployment and employment persistence is unlikely to be found in one industry or sector of the economy.

Next, I decompose unemployment into separation and job-finding rates. While there is strong evidence of a change in the cyclical behavior of job finding occurring at the same time as the change in unemployment behavior, there is little evidence of a change in the persistence of separations. As a result, a decomposition of the impulse response function for aggregate unemployment shows that almost all of the increase in unemployment persistence owes to an increase in the persistence of job finding rates.

In addition, I decompose unemployment into job-loser unemployment and other types of unemployment (new entrants, reentrants or quits). I only find strong evidence for a break in the cyclical behavior of job-loser unemployment. Not surprisingly, a

[2] Other papers have focused on recent changes in certain aspects of the labor market, including an alteration in the correlation between productivity and unemployment, see Barnichon (2010) and increases in the mean duration of unemployment, see, for example, Abraham and Shimer (2001).

decomposition of the impulse response function for aggregate unemployment shows that the break in the behavior of job-loser unemployment largely accounts for the increased persistence of aggregate unemployment.

Finally, I examine the components of job-loser unemployment and show, using a decomposition of the impulse response function, that its increased persistence owes primarily to an increase in the persistence of permanent (as opposed to transitory) job-loser (or layoff) unemployment. To arrive at this last result, I control for a change in the Current Population Survey's (CPS) classification of temporary layoff unemployment beginning in 1994 by adjusting the pre-1994 data on temporary layoff unemployment to make it consistent with the data beginning in 1994. To accomplish this, I randomly switch individuals classified as being on temporary layoff in order to match the relationship between the duration of temporary layoff unemployment and the unemployment rate exhibited after 1994.

Putting these pieces together, prior to the mid to late 1980s, shocks to unemployment left no imprint on the cyclical level of the unemployment rate after 6 quarters. Since then, the behavior of cyclical unemployment has been much different, with impulse responses still positive up to 3 years after the shock. This suggests that either the type of shock affecting the economy is much different now than previously or that the economy's responses to shocks are fundamentally altered. At the same time, greater persistence has been most strongly manifested in job finding rates and permanent layoff unemployment, a combination which suggests that the welfare cost of cyclical increases in unemployment is becoming more concentrated among permanent job losers with extended periods of unemployment.

The next section describes movements in unemployment and employment over the post WWII period and shows that since the late 1980s cyclical movements in these variables appear to have become more persistent. Section 3 formally tests this hypothesis. Section 4 shows that increasing employment persistence has been a feature of most industries and that increased persistence in job finding and permanent layoff unemployment are most responsible for the increase in unemployment persistence. Section 5 discusses the above findings, and section 6 concludes.

2. Cyclical Movements in the Unemployment Rate

Casual observation of unemployment rate movements over the post WWII period suggests that cyclical movements have become more persistent. Panel A of figure 1 shows that beginning with the 1981-82 recession, and to a greater extent in the two subsequent recessions, the unemployment rate seemed to persist at a relatively high level for a longer period of time.

Although business cycle movements appear to dominate movements in unemployment, both lower and higher frequency movements also appear to be important. To abstract from noncyclical changes in the unemployment rate, Panel B of figure 1 shows only the cyclical component of the unemployment rate (having a period from 1-1/2 to 8 years), as constructed with the Baxter-King (BK) band pass filter, see Baxter and King (1999) and the Christiano-Fitzgerald (CF) filter, see Christiano and Fitzgerald (2003). Again more recent cycles—those after the early 1980s—appear to be stretched out relative to prior cycles.

An alternative perspective on these points comes from autocorrelation functions of cyclical movements in unemployment. Figure 2 shows that cyclical unemployment rate movements are positively correlated for longer spans of time after the mid 1980s than before. The change in the shape of the autocorrelation function suggests that after the mid 1980s cyclical fluctuations in unemployment lacked a higher frequency component present in earlier data. To illustrate this more clearly, figure 3 shows an estimated normalized population spectrum for cyclical movements in the seasonally adjusted unemployment rate, where the spectrum at frequency ω is

$$S_{\omega} = \sum_{i=0}^{T/2} \hat{\gamma}_i e^{-i\omega\pi} \tag{1}$$

$\hat{\gamma}$ is the estimated correlation between y_t and y_{t-i}, and y is the cyclical component of the unemployment rate. For the period prior to the mid 1980s, the periodic component of the unemployment rate with the highest relative variance is around 5 years and components from around 2.5 years to 5 years still have substantial relative variance. After the mid 1980s, the peak is shifted to the left and is much higher than previously. In addition, the variances of components around a period of 2.5 years are now negligible.

3. Estimating a Break in the Behavior of Unemployment and Employment

To estimate more precisely the magnitude and statistical significance of the changes in the behavior of the unemployment rate described above, I parameterize the time series process for changes in the unemployment rate and test for breaks in these parameters. I use the band-pass filtered unemployment rate—rather than changes in unemployment—because it is important to filter out both very high and very low frequency movements in unemployment. Filtering out low frequency movements prevents one from confounding changes in the cyclical behavior of unemployment with changes in the magnitude of low frequency unemployment movements. Both first differencing and a band pass filter remove low frequency movements. However, the BK band pass filter is more robust, as it can accommodate processes that are integrated above order 1.

Filtering out high-frequency movements is important because it eliminates high-frequency volatility (an important component of which is likely measurement error) that can make it difficult to identify breaks in the behavior of the cyclical component. While band pass filtering eliminates the high frequency component, first differencing typically accentuates it.[3]

I consider two types of band-pass filters, the BK symmetric band pass filter that uses a fixed window (e.g. 25 quarters) and constant weighting to filter the data, and the CF asymmetric random walk band-pass filter which uses the entire sample and varying weights. The BK filter can accommodate I(2) processes, while the CF filter, as the name implies, assumes the process is a random walk.[4] The two filters give very similar estimates.[5] I also consider definitions of cyclical frequencies that are somewhat lower

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[3] Suppose for example that one first differences the following AR(1) process: $y_t = \rho y_{t-1} + \varepsilon_t,\ \ \varepsilon_t \sim i.i.d.\left(0, \sigma_\varepsilon^2\right),\ \rho > 0$. The population spectrum of the original series is $\frac{1}{2\Pi}\left(\frac{1}{\left(1+\rho^2 - 2\rho\cos(\omega)\right)}\right)$, which decreases as ω increases. First differencing y creates a new series $z_t = y_t - y_{t-1}$, whose population spectrum is $\frac{1}{2\Pi}\left(\frac{1}{\left(1+\rho^2 - 2\rho\cos(\omega)\right)}\right)\left(2\left(1-\cos(\omega)\right)\right)$. The second term increases as the frequency increases, giving higher weight to high frequency components.

[4] If one specifies the statistical process underlying a series, one can use the Christiano-Fitzgerald filter for any statistical process.

[5] Because it is implemented as a centered 25-quarter moving average, the BK filter cannot produce estimates of cyclical unemployment after 2007 (or before 1951). The CF filter can filter an entire sample. However, the information used at the end of the sample is much more limited. With this more limited information, the CF filter implicitly assumes that most of the increase in unemployment since 2007 is very long lasting and of a frequency lower than cyclical. Moreover, this lower frequency, or secular, component is estimated to have continued to increase through 2010. As a result, cyclical unemployment, is estimated to have declined in magnitude noticeably recently, as more of the increase is deemed to have been lower frequency. However, the assumption that secular unemployment has risen rapidly over the past three years is questionable and one must be careful in interpreting it. If one assumed, for example, that unemployment would soon reverse much of its increase, then the filter's estimate of cyclical unemployment would be larger, as would the persistence of the cyclical component, as movements that had deemed lower frequency

than typical. More specifically, the literature typically considers periods from 6 quarters to 32 quarters as cyclical. I use this definition, but I also examine results for filters that define cyclical as having a period from 6 quarters to 40 quarters. Under this definition, lower-than-cyclical frequency, or trend, movements in unemployment are smoother and may correspond more closely to some observers' notions of the distinction between cyclical and secular.

Once I have an estimate of cyclical unemployment in hand, I need to estimate its persistence. To do this, I parameterize the series as an AR(2) process. In making this selection, I am guided by two criteria: (1) that the specification captures most cyclical movements in unemployment and (2) that the specification not lead to implausibly small shocks. While various information criteria would recommend including more lags, an expansion to more lags takes the R^2 of the model very close to 1 and reduces the variance of shocks to trivial levels. Because this goes against a prior that cyclical movements are initiated by substantial changes in the economic environment, I choose to keep the specification relatively spare.[6] However, even an AR(2) process has an R^2 of over .97. Thus, I estimate the following process

$$u_t = \alpha + \sum_{i=1}^{2} \beta_i u_{t-i} + \varepsilon_t \qquad (2)$$

using data from 1951 to 2007 (Three years at each end of the sample is needed to implement the band pass filter.[7])

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were recognized as being cyclical. Rather than taking a stand on what will happen to the unemployment rate in coming years, I only consider filtered estimates through 2007. Of course, it will be very interesting to update these results as more information about the permanence of recent increases is obtained.

[6] Nevertheless, even with the inclusion of several more lags, results are not qualitatively changed.
[7] When the cycle is allowed to have a maximum period of 10 years I use an 8 year moving average to filter the data and the sample is reduced to 1952 to 2006.

I test for a change in persistence by testing whether there is a break in the coefficients governing the movement of cyclical unemployment, and, if so, whether this break produces a more persistent response to shocks. I first treat the break point as exogenous, using the McConnell and Perez-Quiros' estimate (1984Q1) of the break in the volatility of economic activity. This would be appropriate if the change in the persistence of cyclical unemployment rate movements were closely connected to the change in the volatility of various measures of economic activity documented by Stock and Watson (2003) and Ahmed, Levin and Wilson (2004), among others. Table 1 shows estimates of parameters before and after this exogenous break date, as well as F tests, for the three possible break configurations. Because results using the CF filter are qualitatively similar, I only report results using the BK filter. I use the White/Huber robust estimator of the variance of parameters.[8] All three breaks are significant at conventional levels, and all three result in an increase in parameters that should lead to greater persistence. I examine changes in impulse response functions more closely below.

The exogenous break point for volatility in economic activity may not be closely tied to breaks in the persistence of unemployment rates. Indeed, recent events (an increase in economic volatility and an apparent continued persistence in unemployment rate movements) suggest that the two phenomena are distinct. In this case, a more appropriate test would be an Andrews sup Wald test, which chooses the break point as the maximum Wald statistic over some proportion of the sample and uses critical points for this statistic provided by Andrews (1993). Following standard practice, I search for a

[8] Because the variance of shocks is likely to have changed over the sample period, controlling for heteroscedasticity is important.

break over the middle 70 percent of my sample. Again I estimate breaks for each combination of parameter breaks and use robust estimators of parameter variances.

Table 2 reports the relevant statistics and the estimated break point for each test for several specifications of cyclical unemployment (e.g BK with a maximum period of 8 years, CF with a maximum period of 10 years, etc). Assuming a maximum cyclical period of 8 years and using the BK filter, estimated break dates are 1988Q1 for a break in first lag and breaks in both lags and 1987Q2 for a break in the second lag. These breaks are all highly significant. Using the CF filter the date for all three breaks is 1984Q4, and the breaks are again all highly significant. Using a 10 year maximum cyclical period, the estimated break dates are quite similar, except for the break date of the second lag, which is estimated to occur in the mid 1970s. Again, all estimated breaks are highly significant.

Figure 4 shows the impulse responses implied by the pre and post break coefficients using the BK 8 year filter (assuming a break in both coefficients). In the pre-break period, the effect of a shock to the unemployment rate remains positive for about 6 quarters and is statistically significant for 5 quarters. In the post break period, the effect of a shock remains positive for 12 quarters and is statistically significant for 9 quarters.[9] Table 3 shows the difference in the pre and post break IR functions along with bootstrapped 95 percent confidence intervals for each type of filter. For all specifications, the difference in pre and post IR functions is large and significantly different from 0 through step 11.

The third column of table 2 shows that there also appear to be several secondary breaks in the parameters determining cyclical movements in the unemployment rate.

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[9] Results are qualitatively similar using the 10 year filter.

The first secondary break occurs around the mid 1970s and the second in the early 2000s. An examination of the pre and post break coefficients reveals that these secondary breaks also resulted in more persistent movements in cyclical unemployment. These results suggest that there was an ongoing increase in unemployment persistence beginning in the mid 1970s and lasting through the early 2000s.

Because cyclical movements in unemployment and employment are closely related, a change in the persistence of unemployment suggests a similar change in employment. To see if this is the case, I estimate a regression similar to (2) for the cyclical component of private nonfarm employment. Estimates of private nonfarm employment come from the BLS's Current Employment Statistics (CES) survey. Again I use a band pass filter to isolate the cyclical component, and, as with unemployment, the sample extends from 1951 to 2007.

Table 4 shows changes in coefficients assuming an exogenous break date of 1983Q4, and Sup Wald tests for breaks in the various combinations parameters are shown in table 5. As with unemployment, all breaks are highly significant. The second column of table 5 shows that estimated primary break dates for employment are somewhat later than those for unemployment, occurring in the early to mid 1990s, as opposed to the mid to late 1980s. The panels of figure 5 plot implied impulse responses before and after the 1991Q4, the estimated break date when using the BK filter with a maximum period of 8 years. It shows clearly that cyclical movements in employment have become more persistent. Table 6 shows that the difference between pre and post break impulse responses remains positive and statistically significant through step 10 for all specifications. For some specifications and parameter breaks, impulse responses are positive and statistically significant through step 12. Similar to unemployment, there also appear to be secondary breaks. Again these secondary breaks occur in the early to mid 1970s and in the early 2000s.

In sum, cyclical movements in unemployment and employment have become much more persistent over the post WWII period. The timing of the increase in persistence is not clear. While the primary break dates for unemployment occur in the mid to late 1980s, there are secondary breaks suggesting that the increase in persistence has been ongoing since around the mid 1970s.

4. Why Has Cyclical Movements in Unemployment Become More Persistent?

Next I examine various components of unemployment (and employment) to see if the break in persistence has been concentrated in certain areas. To simplify the analysis, I focus on results using the BK filter with a maximum period of 8 years. Results with other filters are qualitatively similar.

4.1 Employment by Industry

First, using employment data from the CES, I examine whether the break in persistence has been concentrated by industry. The sample period is again 1951 to 2007. I estimate separate regressions for the following 8 1 digit industries: construction, manufacturing, professional and business services, trade and transportation, education and health services, leisure and hospitality, financial activities, and other services. The statistical significance of breaks in various combinations of parameters, given an exogenous break date of 1991Q4 (the date estimated using private nonfarm employment), are shown in table 7. Five of the industries—construction, manufacturing, trade and transportation, professional business services, and leisure and hospitality—have breaks significant at the 1 percent level. The implied impulse responses before and after 1991Q4 for each industry are shown in figure 6. For the 5 industries with significant breaks, cyclical movements in employment have become more persistent. For industries without significant breaks, persistence has either changed little (other services and education and health services) or diminished (financial activities). These industries account for an average of only about 20 percent of private nonfarm payroll employment over this period. In sum, the change in persistence appears to be quite broad based, affecting industries accounting for a large majority of private nonfarm employment.

4.2 Separations and Job Finding

Next, following Fujita and Ramey (2009) I take a log linear approximation of the steady state unemployment rate to decompose the unemployment rate into the sum of the rate of flows from employment to unemployment (separations) and the rate of flows from unemployment to employment (job finding).

$$u_t \approx \frac{s_t}{s_t + f_t} \approx \left(1-\overline{u}\right)\overline{u}\left(\hat{s}_t - \hat{f}_t\right),\ \ \overline{u} = \frac{\overline{s}}{\overline{s}+\overline{f}} \qquad (3)$$

where s is separations, f is job finding, hats over variables indicates the log deviation from sample averages, and bars indicate sample averages.[10] Equation (3) uses three approximations: first, the unemployment rate is equated to the steady state unemployment rate; second, the log linear approximation around the average steady state unemployment rate is equated to the steady state unemployment rate; and third, the steady state unemployment rate assumes no flows into and out of the labor force. Nevertheless, the error introduced by each of these approximations is typically quite small, and Shimer (2007) shows that these approximations work quite well empirically.

[10] I measure separations and job finding rates as in Shimer (2007).

The actual and filtered series are shown in figure 7. Both series have significant cyclical movements, though fluctuations in job finding are larger. Table 8 shows F statistics for breaks in various combinations of parameters. Here the exogenous break date is 1988:Q1, the break date estimated for unemployment. There is strong evidence of a break in the behavior of job finding (either the first or the second lag) and some evidence of a break in the behavior of separations (the first lag).[11]

Figures 8 and 9, which plot impulse response functions before and after 1988Q1, show that job finding became considerably more persistent after 1988 and separations only slightly more persistent. This, together with the impression conveyed by figure 7 that job finding accounts for the larger share of the cyclical volatility in unemployment, suggests that changes in the behavior of job finding have likely contributed more to the greater persistence in the aggregate unemployment rate than separations.

To see if this is the case, I decompose the change in the impulse response function for unemployment (from pre to post 1988) into a component due to the break in the behavior of separations and a component due to the break in the behavior of job finding. Note that one can express the unemployment rate as the infinite moving average of innovations to the separations contribution plus the infinite moving average of innovations to the job finding contribution.[12]

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[11] When break dates are estimated, the break in separations occurs somewhat earlier than the estimated break date for unemployment, but the break date for job finding occurs at the same time as that for unemployment.

[12] This assumes that the roots of $1-\sum_{i=1}^{2}\beta_i^s L^i$ and $1-\sum_{i=1}^{2}\beta_i^f L^i$ lie outside the unit circle.

$$
\begin{aligned}
s_t &= \sum_{i=1}^{2} \beta_i^s s_{t-i} + \varepsilon_t^s,\ \varepsilon_t^s \sim i.i.d.\left(0, \sigma_{\varepsilon^s}^2\right) \\
f_t &= \sum_{i=1}^{2} \beta_i^f f_{t-i} + \varepsilon_t^f,\ \varepsilon_t^f \sim i.i.d.\left(0, \sigma_{\varepsilon^f}^2\right) \\
u_t &= s_t + f_t = \left(C(L)\varepsilon_t^s + D(L)\varepsilon_t^f\right) \\
C(L) &= \frac{1}{1-\sum_{i=1}^{2}\beta_i^s L^i};\ D(L) = \frac{1}{1-\sum_{i=1}^{2}\beta_i^f L^i}
\end{aligned}
\tag{4}
$$

If ε_t^s and ε_t^f are perfectly correlated, this becomes

$$
u_t = \left(C(L)\sigma_{\varepsilon^s} + D(L)\sigma_{\varepsilon^f}\right)\varepsilon_t,\ \ \varepsilon_t^s + \varepsilon_t^f = \varepsilon_t \sim i.i.d.(0,1) \tag{5}
$$

and impulse responses from (5) should match those implied by (2) exactly. If ε_t^s and ε_t^f are not perfectly correlated, then the moving average coefficients in (5) will be different than those implied by (2) and will generally provide a more accurate representation of *u* because they take into account the different time series properties of the series underlying *u*.[13] In any case, (5) can be interpreted as the impulse response function of the unemployment rate in response to simultaneous shocks to separations and job finding.

Because changes in the relative variances of the two components can also change the combined impulse response function, I also tested for breaks in the variances of the shocks to both series. There is evidence of a change in the variance of both shocks to separations and shocks to job finding. Thus, prior to 1988, I use $\sigma_{i,pre1988Q1}$, *i=s, f*, in (5) and after 1988, I use $\sigma_{i,post1988Q1}$, *i=s, f*. In addition, to render impulse response functions

[13] When ε^s and ε^f are orthogonal, for example, and for simplicity if u , *s*, and *f* are AR(1) processes, then the moving average representation implied by (2) will be $u_t = A(L)\eta_t$, with $A(L) = \frac{1}{1-\beta^u}$, where

$$\beta^u = \frac{\sigma_s^2}{\sigma_s^2+\sigma_f^2}\beta^s + \frac{\sigma_f^2}{\sigma_s^2+\sigma_f^2}\beta^f$$, and $C(L) = \frac{1}{1-\beta^s}$ and $D(L) = \frac{1}{1-\beta^f}$.

more comparable pre and post break, I multiply the pre-break innovation by the ratio of the post-break to pre-break variances of the innovation, so that the variance of the pre and post break innovations are similar. Thus, rewriting (5) to distinguish behavior before and after the break, one gets

$$\begin{aligned} u_t^{pre} &= \left(\sigma_{\varepsilon^s}^{pre} * C^{pre}(L) + \sigma_{\varepsilon^f}^{pre} * D^{pre}(L)\right) * \frac{\sigma_{\varepsilon^s}^{post} + \sigma_{\varepsilon^f}^{post}}{\sigma_{\varepsilon^s}^{pre} + \sigma_{\varepsilon^f}^{pre}} \varepsilon_t \\ u_t^{post} &= \left(\sigma_{\varepsilon^s}^{post} * C^{post}(L) + \sigma_{\varepsilon^f}^{post} * D^{post}(L)\right) * \varepsilon_t \end{aligned} \tag{6}$$

Normalizing the shock to 1, the impulse response function is

$$\begin{aligned} IR_t^{pre} &= \sigma_{\varepsilon^s}^{pre} \left(\frac{\sigma_{\varepsilon^s}^{post} + \sigma_{\varepsilon^f}^{post}}{\sigma_{\varepsilon^s}^{pre} + \sigma_{\varepsilon^f}^{pre}}\right) * C_i^{pre} + \sigma_{\varepsilon^f}^{pre} \left(\frac{\sigma_{\varepsilon^s}^{post} + \sigma_{\varepsilon^f}^{post}}{\sigma_{\varepsilon^s}^{pre} + \sigma_{\varepsilon^f}^{pre}}\right) * D_i^{pre} \\ IR_t^{post} &= \sigma_{\varepsilon^s}^{post} * C_i^{post} + \sigma_{\varepsilon^f}^{post} * D_i^{post} \end{aligned} \tag{7}$$

where C_i and D_i represent the coefficients on the *i*th lag of MA representations of separations and job finding unemployment, respectively, and where C_i, for example, is defined by the recursion

$$\begin{aligned} C_0 &= 1 \\ C_1 &= \beta_1^s C_0 \\ C_i &= \sum_{j=1}^{2} \beta_j^s C_{i-j},\ i > 1 \end{aligned} \tag{8}$$

The line with circles in Figure 10 shows IR^{pre}, and the line with diamonds shows IR^{post}. Equation (9) describes what the post 1988 IR would have been if only the relative variance of the two components had changed.

$$IR_t^{post,\mathrm{var}} = \sigma_{\varepsilon^s}^{post} * C_i^{pre} + \sigma_{\varepsilon^f}^{post} * D_i^{pre} \tag{9}$$

Since the difference between this and IR^{pre} is imperceptible, it is excluded from the chart.

The line with triangles shows what the post-1988 impulse response would have been had only the relative variances and the behavior of separations changed, equation (10).

$$IR_i^{post,s} = \sigma_{\varepsilon^s}^{post} * C_i^{post} + \sigma_{\varepsilon^f}^{post} * D_i^{pre} \tag{10}$$

The figure shows that the contribution of separations to the change in the *IR* function is relatively slight.

The line with squares shows what the post 1988 impulse response would have been if only the relative variances and the behavior of job finding had changed, equation (11).

$$IR_i^{post,f} = \sigma_{\varepsilon^s}^{post} * C_i^{pre} + \sigma_{\varepsilon^f}^{post} * D_i^{post} \tag{11}$$

The chart reveals that almost all of the change in the impulse response function for unemployment owes to the changed behavior of job finding.

4.2 Layoff and Other Unemployment

Next, I decompose unemployment into categories based on individuals' stated reasons for unemployment. Reason for unemployment data begin in 1967, which shortens the sample considerably. Again, I use an exogenous break date of 1988Q1.

I first distinguish between job loss and other reasons for being unemployed. There are likely significant differences between these two types of unemployed workers. First, as their classification implies, job losers' change in labor force status was likely due to a change in their firms' relative profitability or efficiency. Other types of unemployed individuals were either out of the labor force or quit their previous jobs, and thus their change in status may be more related to changes in household circumstances. Second, job losers are more attached to the labor force than other unemployed individuals: Matched CPS data show that hazards for exiting the labor force are much lower for job losers than for other types of unemployed workers. As a result, the behavior of job losers is more likely to be affected by changes in the relative advantages of employment and unemployment, while the behavior of other types of unemployment is more likely to be affected by changes in the relative advantages of being in or out of the labor force. Nevertheless, both types of unemployed are likely affected by cyclical changes in labor demand.

The top panel in figure 11 graphs cyclical components of job loser and other unemployment as a percent of the labor force. Although both series are procyclical, job loser unemployment shows larger cyclical swings and appears to follow the cyclical pattern of the aggregate unemployment rate more closely. Table 9 shows test statistics for breaks in parameters given an exogenous break date of 1988Q1. For job losers, there is strong evidence of a break in the first, second and both lags. In contrast, there is very little evidence of a break in the behavior of other unemployment. Pre and post break impulse responses, shown in Figures 12 and 13, reveal that only job loser unemployment became significantly more persistent after 1988Q1.

Again, I decompose the change in the IR function for unemployment into layoff and other components using an equation analogous to (4). Figure 14 shows that the change in the impulse response function from pre 1988, the line with the circles, to post 1988, the line with the diamonds, is predominantly due to changes in the impulse response function for layoff unemployment, the line with the squares. The change due to a change in relative variances, the line with the Xs, and to the change in the impulse response function of other unemployment, the line with the triangles, is relatively small.

4.3 Temporary and Permanent Layoff Unemployment

The CPS also distinguishes between temporary layoff unemployment and permanent layoff unemployment. These two series are shown in the bottom panel of figure 11. The behavior of both components appears to have changed noticeably after the mid 1980s. Table 10 shows F statistics for the various combinations of parameter breaks for an exogenous break date (again 1988Q1). The table shows that there were statistically significant changes in the behavior of both components of layoff unemployment.

One problem with interpreting these results is that there was a significant change in the classification of temporary layoff unemployment beginning in 1994, which makes inference about changes in the behavior of temporary layoff unemployment problematic. The CPS questions used to identify temporarily laid off workers changed with the 1994 CPS redesign. In general, more stringent criteria were used to classify workers on temporary layoff, and, in particular, after the redesign only workers expecting a recall within 6 months are classified on temporary layoff. The post-redesign definition likely limits the values of unemployment duration for temporary job losers that are observed after the redesign compared to prior to the redesign.

Indeed, from figure 15—which shows a time series of the average duration of uncompleted spells of temporary layoff unemployment—it's quite apparent that there is a break in this series in January 1994, with average durations beginning in 1994 much lower than previous durations.[14] Thus, data on the duration of uncompleted spells of

[14] The redesign also led to a break in the duration data. After the redesign, interviewers coded the duration response to be equal to the duration response from the previous interview plus 4 or 5 weeks if the individual was still unemployed. Prior to the redesign, individual's responses were not constrained in this way. To control for this, I follow prior research and use only the 1st and 5th rotation groups to compute

temporary layoff unemployment strongly suggest that the break in classification had a noticeable effect on the types of individuals classified on permanent and temporary layoff.

I use the implied restriction on observed unemployment durations of temporary job losers after the redesign to estimate the probability of being misclassified (according to the post redesign definition) in the pre redesign data. Prior to 1994, the CPS distinguished between individuals on temporary layoff for less than 30 days and job losers on indefinite temporary layoff. The first group would be classified on temporary layoff both before and after the redesign. However, some of the workers in the second group would likely not have been classified on temporary layoff after the redesign. I only estimate misclassification probabilities for the latter individuals.[15]

For these individuals I use information on the duration of uncompleted spells of temporary layoff unemployment after the redesign to identify likely misclassifications (under the redesign definition) of temporary layoff unemployment prior to 1994. My methodology is described in detail in the appendix.

My estimates of the share of temporary job losers that were misclassified are shown in figure 16. The pattern is strongly countercyclical: Misclassification increases in when the unemployment rate rises. To adjust for misclassification prior to 1976, when

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average duration. These groups were not interviewed in the previous month, and thus their duration responses were unconstrained.

[15] Polivka and Millar (1998) provide ratios to adjust the pre-1994 data to make it consistent with data gathered after the redesign. The ratios, which are reported for both permanent and temporary layoff unemployment, were estimated using parallel CPS surveys in 1993. One survey interviewed individual using the redesigned questionnaire and methodology, while another survey used the old method. The ratio of the same statistic from the two surveys is the basis of the Polivka and Millar ratios. However, the assumption underlying adjustment using Povlika/Miller ratios when applied to temporary and permanent layoff unemployment is very strong. In particular, the ratio assumes that the effect of the redesign on the classification of temporarily laid off workers is constant over time. Given that the ratio of permanent to temporarily laid off workers is strongly cyclical, this assumption is highly questionable, at least as applied to temporary and permanent layoff unemployment, and below I show that it is unlikely to hold.

CPS micro data are not available, I use the relationship between misclassification and the unemployment rate from 1976 to 1993 to adjust the pre-1976 data.

$$Mshare_t = \alpha + \beta u_t, \ \ t = 1967, ..., 1975 \qquad (12)$$

where *Mshare* is the share of temporary layoff unemployment that is misclassified (according to the post redesign definition), and α and β are estimated with the 1976-1993 data. The full time series of adjusted temporary layoff unemployment is shown in figure 17, along with the unadjusted series for comparison. The difference between the two series is noticeable, but there is still a significant step down in the relative volatility of temporary layoff unemployment after the late 1980s.

Table 11 shows F statistics and pre and post break coefficient estimates for the different types of parameter breaks. The adjusted data also strongly suggest significant breaks in the behavior of both components. Figures 18 and 19, which plot impulse responses before and after 1988, show that both components became more persistent after 1988, though the change is more noticeable for permanent layoff unemployment.

Figure 20 uses the impulse response decomposition outlined in (4) to illustrate how the changes to the behavior of permanent and temporary layoff unemployment affected the persistence of aggregate layoff unemployment. The reduction in the relative variance of temporary layoff unemployment increased the persistence in layoff unemployment somewhat (the line with Xs). Because temporary layoff unemployment is less persistent than permanent layoff unemployment, a reduction in the relative variance of temporary layoff unemployment led to greater persistence in layoff unemployment. The changed behavior of temporary layoff unemployment also led to a small increase in the persistence of aggregate unemployment (the line with triangles). However, most of the increased persistence of layoff unemployment has been due to the changing behavior of permanent layoff unemployment (the line with squares).

5. Discussion

The above results have some important implications. First, the return of higher volatility during the most recent recession does not necessarily imply a return to less persistent movements in unemployment. Although volatility in economic activity has increased recently, cyclical movements in the unemployment rate have thus far remained quite persistent. After reaching a peak unemployment rate of 10 percent in 2009Q4, the unemployment rate changed little over the course of 2010 and has only recently begun to decline significantly. This suggests that the pattern of more persistent movements in the unemployment rate (and employment) may endure.

Second, the effects of cyclical fluctuations in unemployment on welfare may be greater now than previously. The fact that much of the increased persistence in aggregate unemployment can be explained by increased persistence in job finding rates indicates that an increase in the persistence of individual unemployment spells lies behind the increased persistence of aggregate unemployment. When job finding rates are low, unemployment spells will last longer. The increase in longer lasting unemployment spells implies that the welfare costs of cyclical downturns is likely more unevenly distributed now than previously, assuming that short-duration spells do not affect the same people over and over. This is because persistently low job finding rates imply that unemployment in a recession increasingly consists or a limited number of individuals having long spells of unemployment.[16] If the drop in income due to unemployment is not fully insured against, as suggested by Blundell, Pistaferri, and Preston (2008), and if preferences are concave in consumption, then, as shown in Abraham and Shimer (2001), the greater concentration of unemployment among individuals with relatively long spells reduces social welfare.

Moreover, the individuals incurring these longer spells of unemployment appear to be permanent job losers, as this is the category of unemployment accounting for of the increased persistence of aggregate unemployment. Evidence suggests that wage losses of permanently displaced individuals are often quite large, see Jacobson, Lalonde, and Sullivan (1993) and von Wachter (2008). Thus, welfare loss for these individuals is greater than that coming only from prolonged unemployment. It also likely includes reduced earnings upon reemployment.

Overall, it appears that recessions have changed from relatively short events in which a relatively large number of people suffered relatively short spells of unemployment into longer events, in which relatively fewer people (per cumulative weeks of unemployment) suffer relatively longer spells of unemployment. And those suffering these longer spells are more likely to be permanent job losers, many of whom suffer persistent losses in income.

Third, optimal public policy responses to downturns may also have changed. If periods of reduced economic activity are more protracted, then short bursts of stimulus that shift economic activity over periods that are fairly close in time without leading to a persistent change in the level of activity may not improve welfare. For example, if

[16] If, instead, increased unemployment persistence were due to greater persistence in job separations, this would imply that periods when many individuals have relatively short spells of unemployment (recessions) have become more prolonged.

unemployment remained cyclically elevated from period *t* to period *t+4* prior to the late 1980s and from period *t* to period *t+8* after the late 1980s, then fiscal policy that causes activity to be shifted from period *t+5* to period *t+1* helps to increase welfare prior to the late 1980s, but does not increase welfare after the late 1980s.

6. Conclusion

Cyclical movements in the unemployment rate have become much more persistent over the post World War II period. The greater persistence has been relatively widespread across industries. Increases in the persistence of permanent layoff unemployment and job finding rates appear to account for most of the increased persistence in the aggregate unemployment rate. This combination suggests that the welfare effects of cyclical increases in unemployment may be increasingly concentrated among permanent job losers unemployed for extended durations.

Appendix

To account for the effect of the CPS redesign on the definition of permanent and temporary layoff unemployment, I adjust the pre-1994 data by randomly switching individuals on indefinite temporary layoff in the pre-1994 data to permanent lay off status, choosing the number of individuals to switch so as to match (in each year) the mean durations of uncompleted spells of temporary layoff unemployment, conditional on the unemployment rate. I estimate the relationship between the mean duration of temporary layoff unemployment and the unemployment rate using the post-1993 data. Thus, I choose $\omega_{i,t}$, the probability of switching individual *i* (a job loser on temporary layoff) to permanent layoff status in year *t*, so that

$$\frac{1}{S}\sum_{j=1}^{S}\left(\frac{1}{N}\sum_{i=1}^{N}d_{i,t}*\omega_{i,t}\left(d_{i,t}\right)\right)=E\left(d_t^{temp}\middle|u_t\right) \tag{A1}$$

where *N* is the number of observed individuals on temporary layoff in year *t*, *S* is the number of times I perform the random reassignment in each year, and $d_{i,t}$ is the duration of unemployment for individual *i*. Note that $\omega_{i,t}$ is a function of individual *i*'s observed unemployment duration and that for job losers on temporary layoff for less than 30 days, $\omega_{i,t}=0$.

It is also important to note that the mean duration of unemployment for individuals on temporary layoff, the left hand side of (A1), will be affected by the duration of individuals I switch. That is, if the individuals chosen to be switched have relatively high durations, then fewer individuals will have to be switched in order to reduce the average duration of individuals on temporary layoff to match the right hand side of (A1). In general, the post-1993 data show that as duration increases, the less likely it is that a job loser is on temporary layoff. Thus, I allow the probability of switching an individual *i* to depend on that individual's duration of unemployment. More specifically, the probability of being misclassified as a temporarily laid off worker conditional on having an uncompleted spell of unemployment of length *d* is

$$\omega_{i,t}\left(d_{i,t}\right)=1-prob_{i,t}\left(temp\middle|d_{i,t}=d\right)= \\ 1-\frac{prob\left(d_{i,t}=d\middle|temp\right)}{prob\left(d_{i,t}=d\right)}prob_t\left(temp\right)=1-\theta_{i,t}*\gamma_t \tag{A2}$$

where

$$\theta_{i,t}=\frac{prob\left(d_{i,t}=d\middle|temp\right)}{prob\left(d_{i,t}=d\right)},\ \gamma_t=prob_t\left(temp\right) \tag{A3}$$

And where $prob\left(temp\right)$ refers to the probability of being on temporary layoff under the post redesign definition. (A2) decomposes $\omega_{i,t}\left(d_{i,t}\right)$ into two components: γ_t, which I will estimate using (A1) and $1-\theta_{i,t}$, which I estimate using the post redesign data on duration and temporary and permanent layoff status.

$$\hat{\theta}_{i,t}=\frac{\sum_{t=1994}^{2009}\sum_{i=1}^{N_t}I\left(d_{i,t}=d\right)*I\left(temp\right)}{\sum_{t=1994}^{2009}\sum_{i=1}^{N_t}I\left(temp\right)*\sum_{t=1994}^{2009}\sum_{i=1}^{N_t}I\left(d_{i,t}=d\right)} \tag{A4}$$

where *I* is an indicator variable equal to 1 if the expression in the succeeding parentheses is true. Note that because individuals on temporary layoff typically have shorter durations, $\theta_{i,t}$ will be larger when duration is smaller and vice versa. This implies that the probability of switching, $\omega_{i,t}$, will be higher for individuals with long durations.

Using (A2-A4) to rewrite (A1) yields

$$\frac{1}{S}\sum_{j=1}^{S}\left(\frac{1}{N}\sum_{i=1}^{N}d_{i,t}*\left(1-\hat{\theta}_{i,t}*\hat{\gamma}_t\right)\right)=E\left(d_t^{temp}\middle|u_t\right) \tag{A5}$$

Thus, I choose $\hat{\gamma}_t = prob_t\left(temp\right)$ for each year, given $\hat{\theta}_{i,t}$, so that the average duration of temporary job losers matches its expected value using the post redesign data.

I use a linear regression of the average duration of uncompleted temporary layoff spells in year *t* on the unemployment rate in year *t* using the post redesign data to estimate

$$E\left(d_t^{temp}\middle|u_t\right)=\alpha+\beta u_t \tag{A6}$$

An example of how I implement my adjustment procedure may help explicate this method. I first estimate $\theta_{i,t}$ using the post redesign data. Then I choose a candidate γ_t for period *t*. Using (A2), I then randomly switch individuals on indefinite temporary layoff to permanent layoff status, where the probability of a switch depends, through $\hat{\theta}_{i,t}$, on their duration of unemployment. With the switches accomplished, I then compute the mean duration of unemployment for temporary job losers (who now exclude the switched individuals). I repeat this procedure 100 times, $S=100$, and take the average of the means and compare the average to the expected value conditional on the time *t* unemployment rate, where the expected values have been computed using the post-1993 data. If the difference is above some tolerance, I repeat the procedure using a different γ_t until convergence is achieved. I repeat this for each period *t*.

Thus, my estimation procedure is an example of indirect inference, see Gourieroux and Monfort (1996). I cannot identify γ analytically using moments from the data because the estimated γ will depend on which individuals are deemed to be misclassified. In effect, there is a latent variable, $\kappa_{i,t}$, such that individual *i*'s misclassification status is $\theta_{i,t}\gamma_t + \kappa_{i,t}$. By taking *S* draws, I, in effect, integrate $\kappa_{i,t}$ out of (A5), enabling estimation of γ_t.

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Table 1. Testing for an exogenous break (1984Q1) in the Behavior of Cyclical Unemployment (Baxter-King filter with maximum cyclical period of 8 years)

	Coefficients with break		
	First lag	Second lag	Both
Pre Break			
First lag	1.73	1.74	1.74
	(.04)	(.03)	(.04)
Second lag	-.91	-.93	-.92
	(.04)	(.04)	(.04)
Post Break			
First lag	1.85	1.74	1.78
	(.04)	(.03)	(.05)
Second lag	-.91	-.81	-.83
	(.04)	(.04)	(.05)
F statistic	28.1**	29.0**	14.77**
R^2	.97	.97	.97

Note. Robust standard error in parentheses. *denotes 5 percent significance. **denotes 1 percent significance.

Table 2. Estimated Breaks in the Behavior of Cyclical Unemployment

Filter, Max. Cyc. Period	Coefficient Break	Estimated Break Period	Secondary Break Periods
BK, 8	1	1988Q1**	1975Q4*, 2004Q1**
BK, 8	2	1987Q2**	1975Q4*, 2004Q2**
BK, 8	1 & 2	1988Q1**	
CF, 8	1	1984Q4**	2003Q4**
CF, 8	2	1984Q4**	2001Q4**
CF, 8	1 & 2	1984Q4**	
BK, 10	1	1987Q4**	1975Q4**, 2002Q3*
BK, 10	2	1975Q4**	
BK, 10	1 & 2	1987Q4**	
CF, 10	1	1987Q1**	1975Q4**, 2002Q3*
CF, 10	2	1975Q4**	
CF, 10	1 & 2	1987Q1**	

Note. *denotes 5 percent significance. **denotes 1 percent significance.

Table 3. Comparing Unemployment Rate IRs before and after break

Specification (Filter, Max. cyc. Period, break date)	Lag break	Difference in Impulse Response Function after break to before break				
		Step 4	Step 6	Step 8	Step 10	Step 12
BK, 8, 1988Q1	1	1.72*	3.21*	3.92*	3.21*	1.26
BK, 8, 1987Q2	2	.92*	2.14*	2.93*	2.64*	1.27
BK, 8, 1988Q1	1 & 2	1.97*	3.54*	4.21*	3.32*	1.09
CF, 8, 1984Q4	1	1.48*	2.67*	3.04*	2.05*	.02
CF, 8, 1984Q4	2	.78*	1.79*	2.35*	1.87*	.44
CF, 8, 1984Q4	1 & 2	1.51*	2.71*	3.07*	2.05*	-.02
BK, 10, 1988Q1	1	1.49*	2.80*	3.46*	2.90*	1.21
BK, 10, 1987Q2	2	.96*	2.11*	2.51*	1.46*	-.59
BK, 10, 1988Q1	1 & 2	1.87*	3.30*	3.88*	3.04*	0.93
CF, 10, 1984Q4	1	1.50*	2.86*	3.64*	3.26*	1.72
CF, 10, 1984Q4	2	1.11*	2.47*	2.95*	1.73*	-.66
CF, 10, 1984Q4	1 & 2	1.89*	3.39*	4.12*	2.64*	1.55

Note. Bootstrapped confidence intervals in parentheses. 200 replications and stratified resampling by the date of the primary estimated break. *denotes that 95 percent confidence interval excludes 0.

Table 4. Testing for an exogenous break (1984Q1) in the Behavior of Cyclical Employment (Baxter-King filter with maximum cyclical period of 8 years)

	Coefficients with break		
	First lag	Second lag	Both
Pre Break			
First lag	1.77	1.78	1.78
	(.03)	(.03)	(.03)
Second lag	-.93	-.95	-.94
	(.03)	(.03)	(.03)
Post Break			
First lag	1.88	1.78	1.85
	(.03)	(.03)	(.04)
Second lag	-.93	-.84	-.91
	(.03	(.03)	(.04)
F statistic	37.6**	32.3**	18.67**
R^2	.98	.98	.98

Note. Robust standard error in parentheses. *denotes 5 percent significance. **denotes 1 percent significance.

Table 5. Estimated Breaks in the Behavior of Cyclical Employment

Filter, Max. Cyc. Period	Coefficient Break	Estimated Break Period	Secondary Break Periods
BK, 8	1	1991Q4**	1975Q4**, 2004Q2**
BK, 8	2	1975Q4**	2001Q4**
BK, 8	1 & 2	1991Q4**	
CF, 8	1	1995Q3**	1970Q2**, 2004Q2**
CF, 8	2	1983Q4**	1970Q3*, 2001Q4**
CF, 8	1 & 2	1996Q1**	
BK, 10	1	1975Q4**	2002Q3*
BK, 10	2	1975Q4**	1961Q4*
BK, 10	1 & 2	1987Q2**	1990Q4*
CF, 10	1	1975Q4**	
CF, 10	2	1975Q4**	
CF, 10	1 & 2	1975Q4**	

*denotes 5 percent significance. **denotes 1 percent significance.

Table 6. Comparing Employment Rate IRs before and after break

Specification (Filter, Max. cyc. Period, break date)	Lag break	Difference in Impulse Response Function after break to before break, 95 percent confidence bands in parentheses				
		Step 4	Step 6	Step 8	Step 10	Step 12
BK, 8, 1988Q1	1	1.55*	3.15*	4.37*	4.42*	3.03*
BK, 8, 1987Q2	2	.79*	1.88*	2.54*	1.99*	.22
BK, 8, 1988Q1	1 & 2	1.68*	3.35*	4.58*	4.57*	3.07*
CF, 8, 1984Q4	1	1.48*	2.95*	3.95*	3.74*	2.14
CF, 8, 1984Q4	2	.66*	1.62*	2.34*	2.18*	1.7*
CF, 8, 1984Q4	1 & 2	1.76*	3.35*	4.33*	3.93*	2.01*
BK, 10, 1988Q1	1	1.59*	2.97*	3.54*	2.59*	.29
BK, 10, 1987Q2	2	.94*	2.31*	3.31*	2.96*	1.04*
BK, 10, 1988Q1	1 & 2	1.64*	3.08*	4.01*	3.75*	2.13*
CF, 10, 1984Q4	1	1.86*	3.44*	4.03*	2.86*	.25
CF, 10, 1984Q4	2	.96*	2.33*	3.24*	1.88*	.74
CF, 10, 1984Q4	1 & 2	1.64*	3.17*	3.83*	1.69*	.34

Note. Bootstrapped confidence intervals in parentheses. 200 replications and stratified resampling by the date of the primary estimated break.

Table 7. Testing for an exogenous breaks (1991Q4) in the Behavior of Cyclical Employment by Industry

Industry	Coefficient Breaks
Construction	1**, 2**, 1&2**
Manufacturing	1**, 2**, 1&2**
Trade and Transportation	1**, 2**, 1&2**
Professional and Business Services	1**, 2**, 1&2**
Leisure and Hospitality Services	1**, 2**, 1&2*
Education and Health Services	1*
Financial Activities	
Other Services	

Note. Baxter-King filter with maximum cyclical period of 8 years. Robust standard errors. *denotes 5 percent significance. **denotes 1 percent significance.

Table 8. Testing for an exogenous break (1988Q1) in the Behavior of Cyclical Separations and Job Finding

	Coefficients with break		
	First lag	Second lag	Both
		Separations	
Pre Break			
First lag	1.62	1.63	1.62
	(.04)	(.04)	(.04)
Second lag	-.91	-.91	-.91
	(.04)	(.04)	(.04)
Post Break			
First lag	1.68	1.63	1.66
	(.04)	(.04)	(.07)
Second lag	-.91	-.85	-.88
	(.04)	(.04)	(.07)
F statistic	4.31*	3.7	2.17
R^2	.95	.95	.95
		Job Finding	
Pre Break			
First lag	1.74	1.76	1.74
	(.03)	(.03)	(.03)
Second lag	-.91	-.93	-.91
	(.03)	(.03)	(.04)
Post Break			
First lag	1.85	1.76	1.85
	(.03)	(.03)	(.05)
Second lag	-.91	-.82	-.92
	(.03)	(.03)	(.05)
F statistic	23.59**	20.31**	3.55
R^2	.98	.98	.98

Note. Baxter-King filter with maximum cyclical period of 8 years. Sample period 1951Q2 to 2007Q4. Robust standard error in parentheses. *denotes 5 percent significance. **denotes 1 percent significance.

Table 9. Testing for an exogenous break (1988Q1) in the Behavior of Cyclical Layoffs and Other Unemployment

	Coefficients with break		
	First lag	Second lag	Both
		Job Loser Unemployment	
Pre Break			
First lag	1.77	1.78	1.75
	(.05)	(.05)	(.05)
Second lag	-.92	-.93	-.91
	(.05)	(.05)	(.06)
Post Break			
First lag	1.87	1.78	1.92
	(.05)	(.05)	(.04)
Second lag	-.92	-.83	-.97
	(.05)	(.05)	(.04)
F statistic	20.8**	15.69**	5.53**
R^2	.98	.98	.98
		Other Unemployment	
Pre Break			
First lag	1.78	1.78	1.78
	(.04)	(.04)	(.05)
Second lag	-.90	-.92	-.91
	(.04)	(.04)	(.05)
Post Break			
First lag	1.82	1.78	1.79
	(.04)	(.04)	(.06)
Second lag	-.90	-.87	-.87
	(.04)	(.04)	(.07)
F statistic	2.52	2.72	1.35
R^2	.98	.98	.97

Note. Baxter-King filter with maximum cyclical period of 8 years. Sample period 1970 to 2007. Robust standard error in parentheses. *denotes 5 percent significance. **denotes 1 percent significance.

Table 10. Testing for an exogenous break (1988Q1) in the Behavior of Cyclical Permanent and Temporary Layoff Unemployment

	Coefficients with break		
	First lag	Second lag	Both
	Permanent Layoff Unemployment		
Pre Break			
First lag	1.81	1.83	1.80
	(.04)	(.04)	(.05)
Second lag	-.94	-.96	-.93
	(.04)	(.04)	(.05)
Post Break			
First lag	1.89	1.83	1.92
	(.04)	(.04)	(.04)
Second lag	-.94	-.89	-.97
	(.04)	(.04)	(.04)
F statistic	15.5**	11.8**	8.1**
R^2	.99	.99	.99
	Temporary Layoff Unemployment		
Pre Break			
First lag	1.70	1.70	1.70
	(.06)	(.06)	(.06)
Second lag	-.89	-.89	-.89
	(.06)	(.06)	(.07)
Post Break			
First lag	1.81	1.70	1.83
	(.06)	(.06)	(.07)
Second lag	-.89	-.79	-.92
	(.06)	(.06)	(.06)
F statistic	14.8**	11.6**	7.75**
R^2	.96	.96	.96

Note. Baxter-King filter with maximum cyclical period of 8 years. Sample period 1970 to 2007. Robust standard error in parentheses. *denotes 5 percent significance. **denotes 1 percent significance.

Table 11. Testing for an exogenous break (1988Q1) in the Behavior of Adjusted Cyclical Permanent and Temporary Layoff Unemployment

	Coefficients with break		
	First lag	Second lag	Both
	Adjusted Permanent Layoff Unemployment		
Pre Break			
First lag	1.80	1.82	1.79
	(.04)	(.04)	(.05)
Second lag	-.93	-.95	-.93
	(.04)	(.04)	(.05)
Post Break			
First lag	1.88	1.82	1.92
	(.04)	(.04)	(.04)
Second lag	-.93	-.88	-.98
	(.04)	(.04)	(.04)
F statistic	16.4**	12.36**	8.7**
R^2	.99	.99	.99
	Adjusted Temporary Layoff Unemployment		
Pre Break			
First lag	1.69	1.70	1.69
	(.06)	(.06)	(.06)
Second lag	-.89	-.90	-.89
	(.06)	(.06)	(.07)
Post Break			
First lag	1.81	1.70	1.83
	(.06)	(.06)	(.06)
Second lag	-.89	-.79	-.91
	(.06)	(.06)	(.05)
F statistic	16.4**	13.7**	8.4**
R^2	.96	.96	.96

Note. Baxter-King filter with maximum cyclical period of 8 years. Sample period 1970 to 2007. Robust standard error in parentheses. *denotes 5 percent significance. **denotes 1 percent significance.

Figure 1. The Behavior of the Unemployment Rate

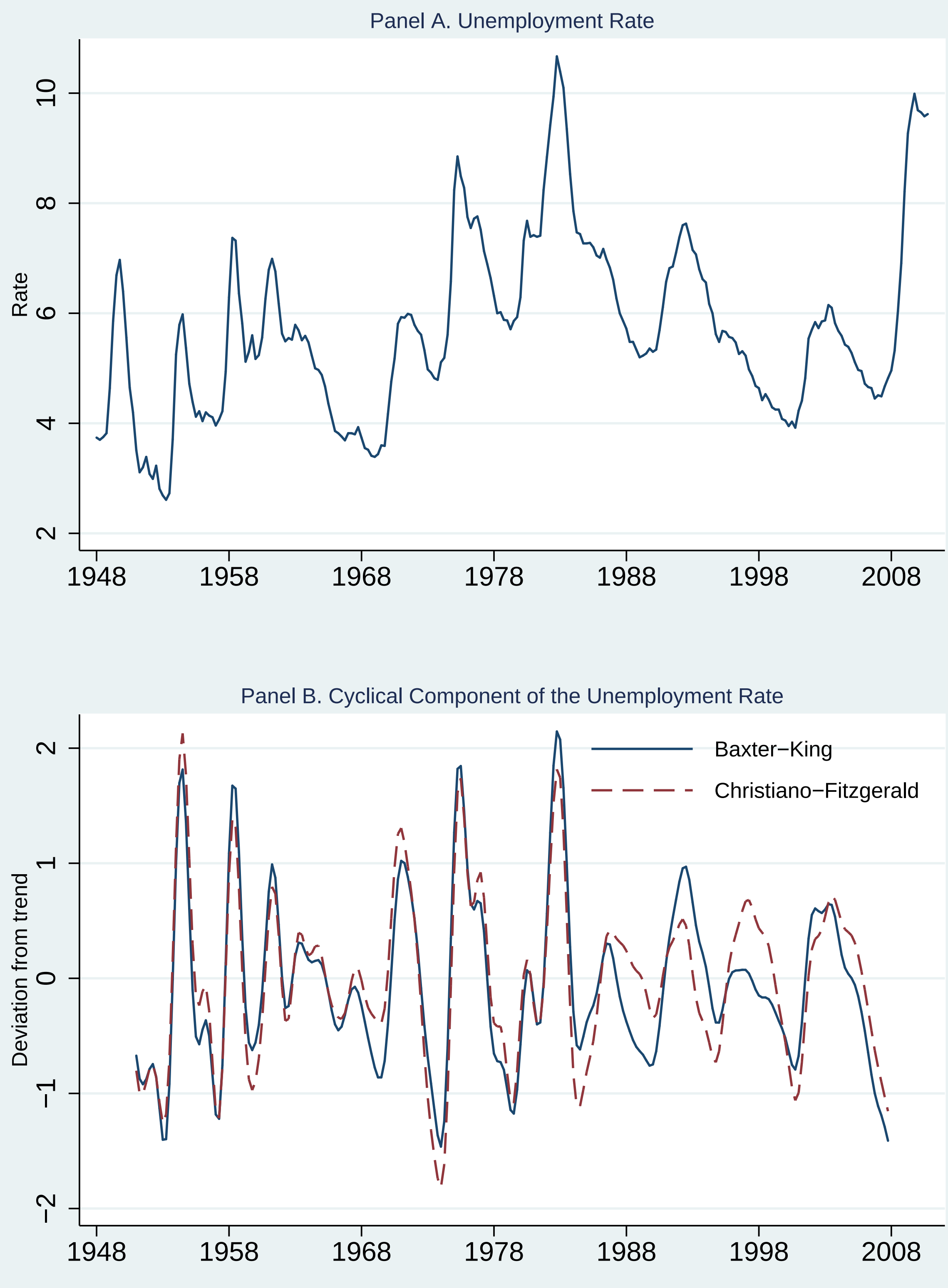


Figure 2. Autocorrelation of Cyclical Unemployment Rate

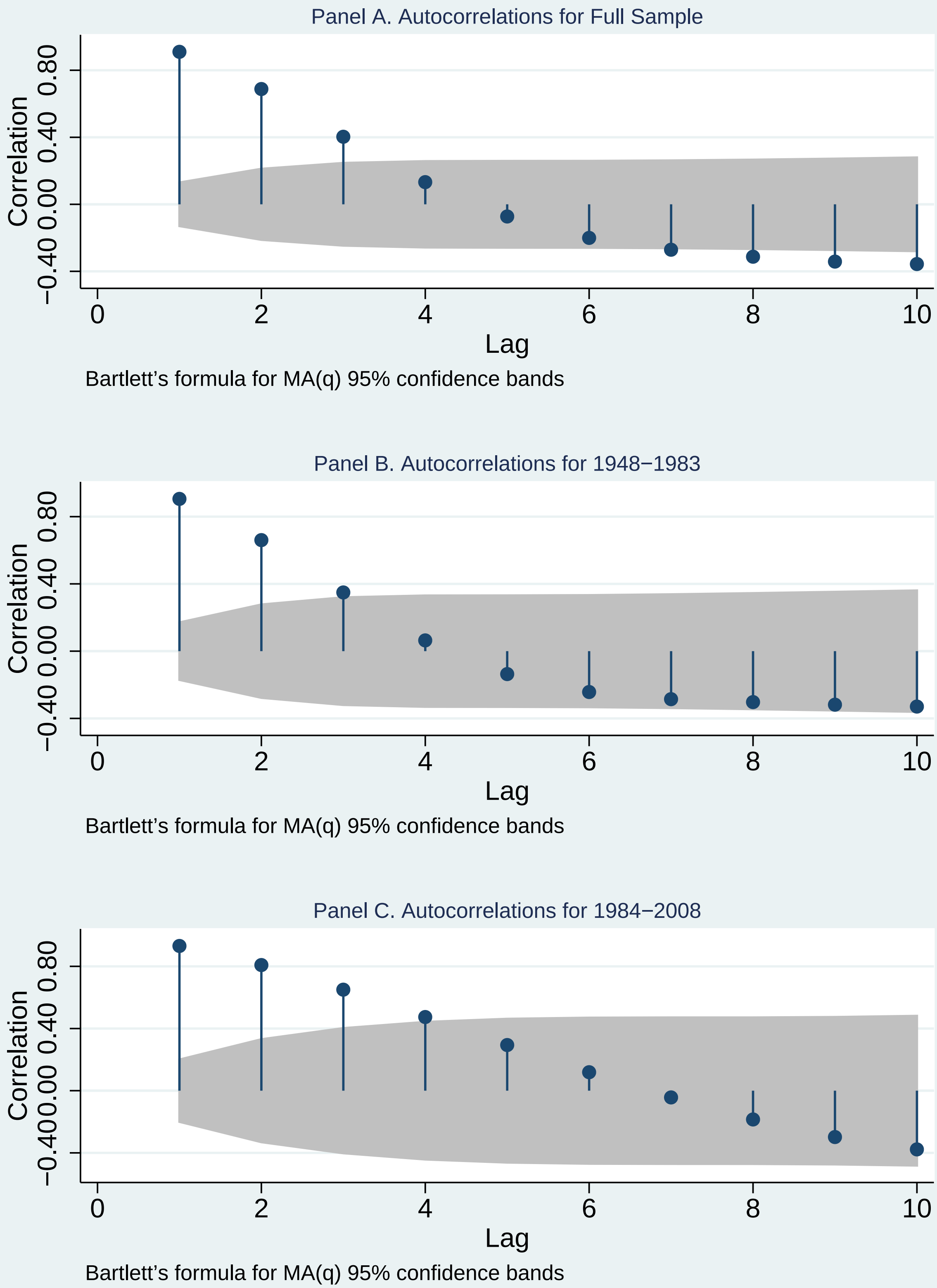
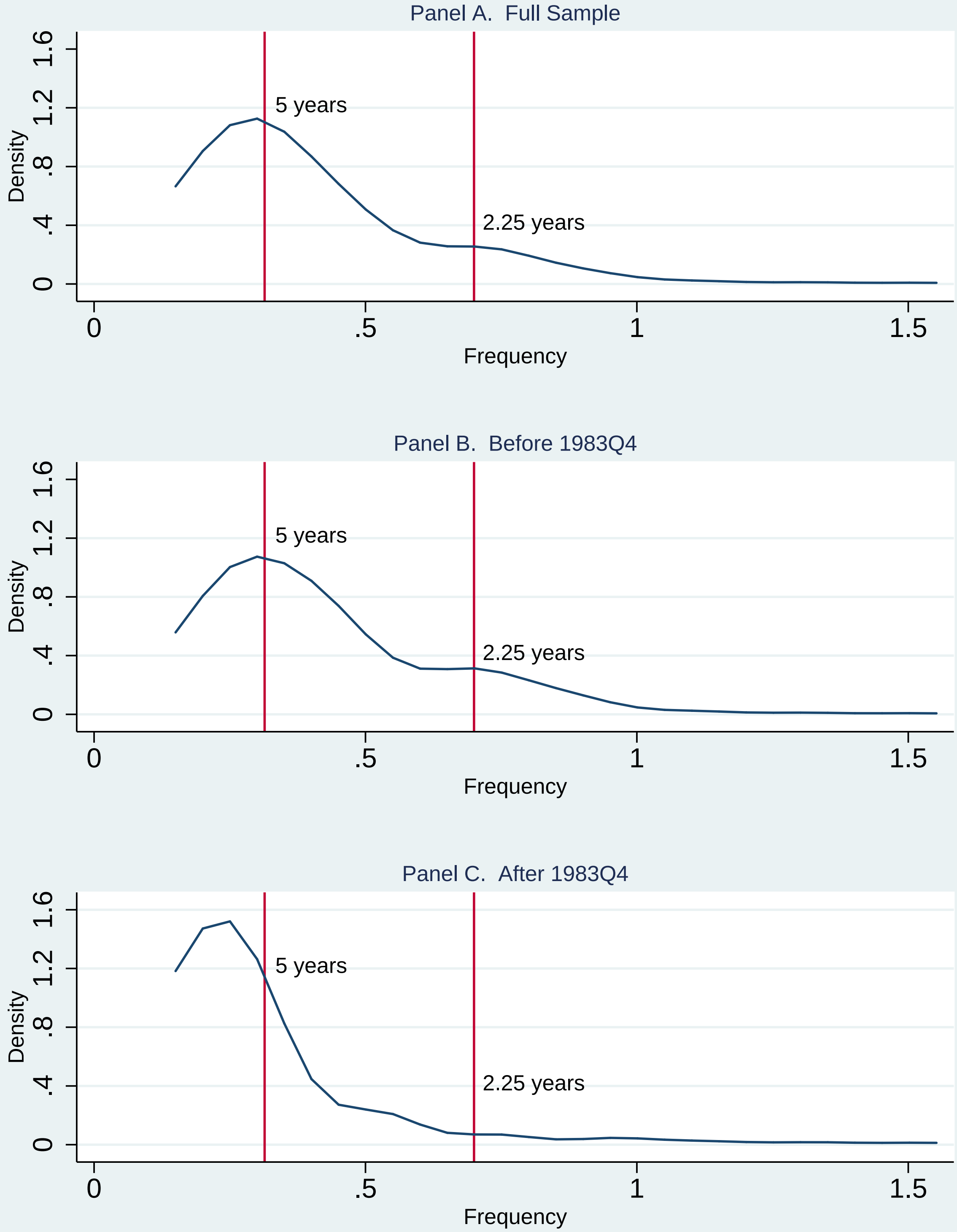
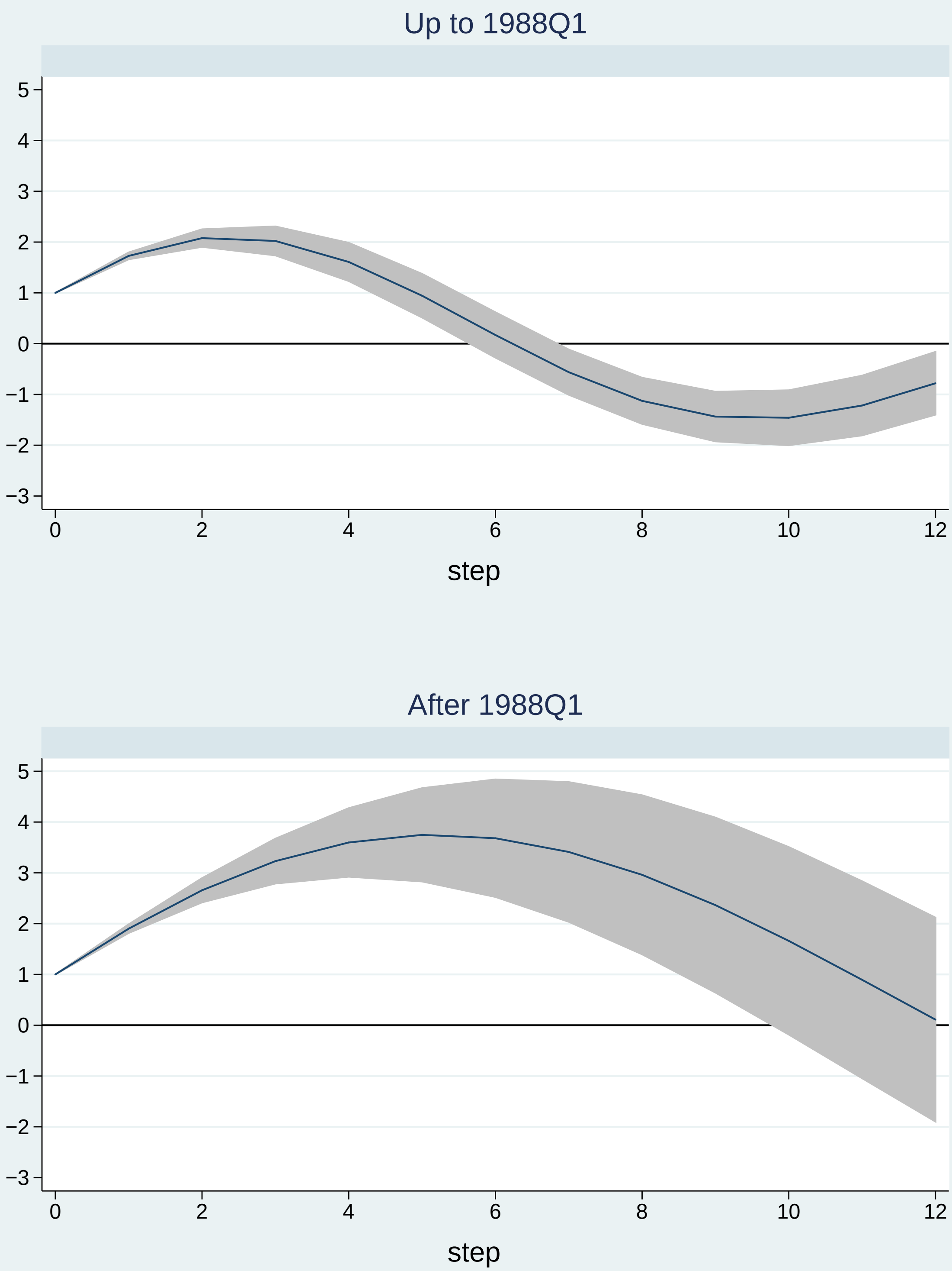


Figure 3. Normalized Population Spectrum of Cyclical Unemployment Rate



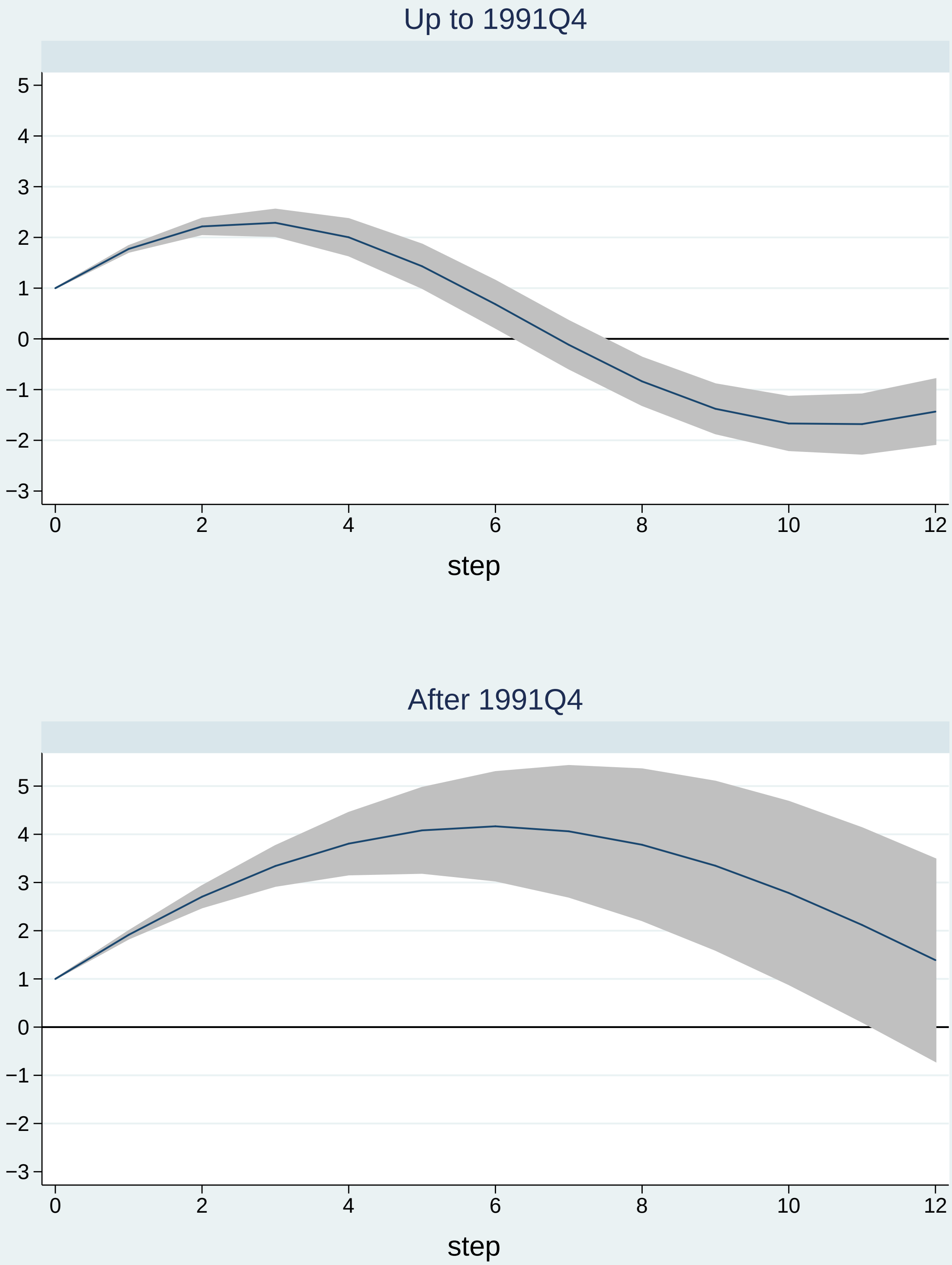
Using BK filter with maximum cylical period of 8 years. Estimated with Bartlett Kernal and bandwidth=32. Period in quarters equals 6.28/frequency, e.g. frequency 0.3 corresponds roughly to a period of 5 years.

Figure 4. Impulse Responses of Cyclical Unemployment Rate



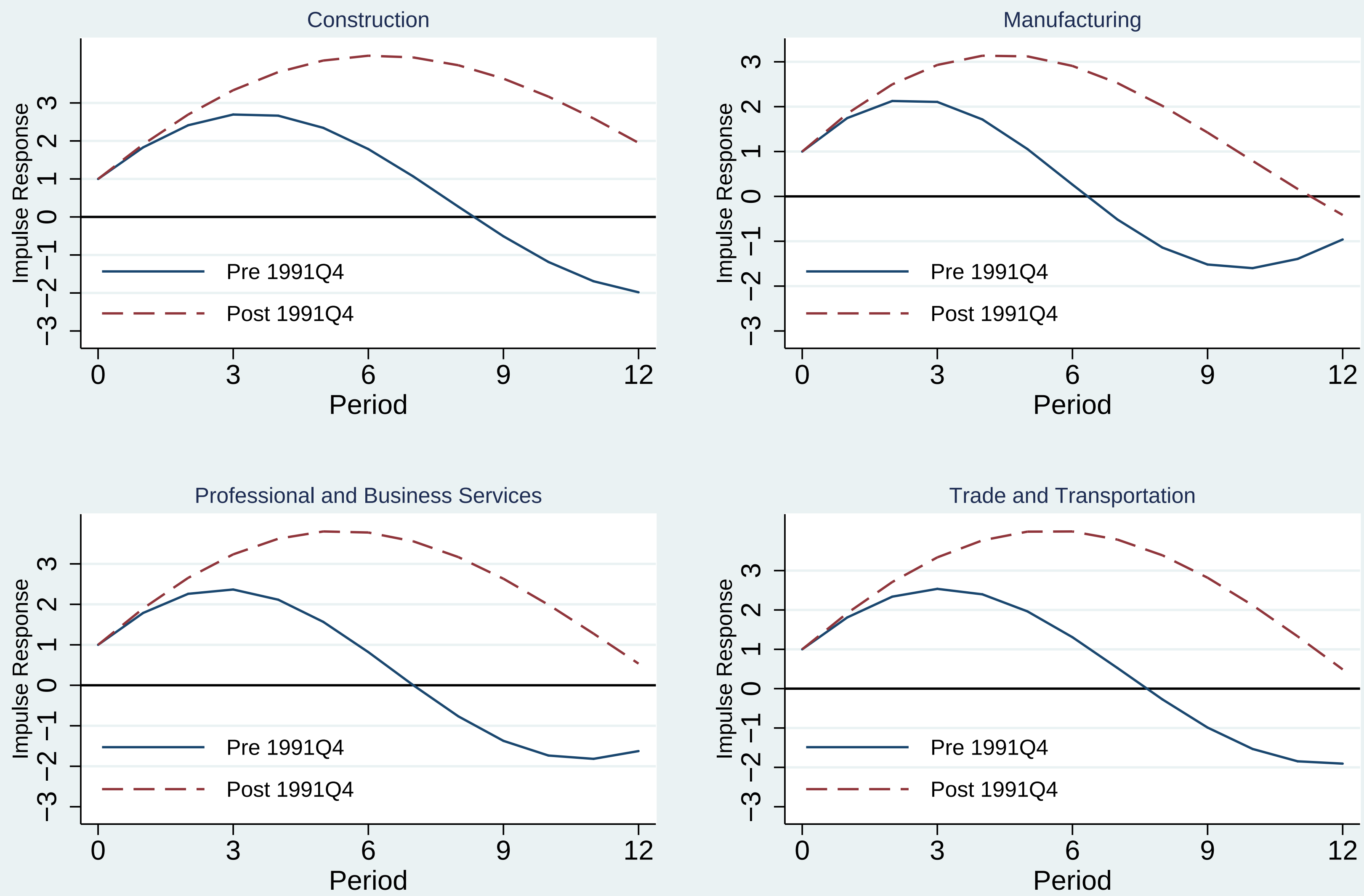
Gray−shaded regions contain 95 percent confidence intervals.

Figure 5. Impulse Responses of Cyclical Employment



Gray−shaded regions contain 95 percent confidence intervals.

Figure 6. Industry Impulse Responses



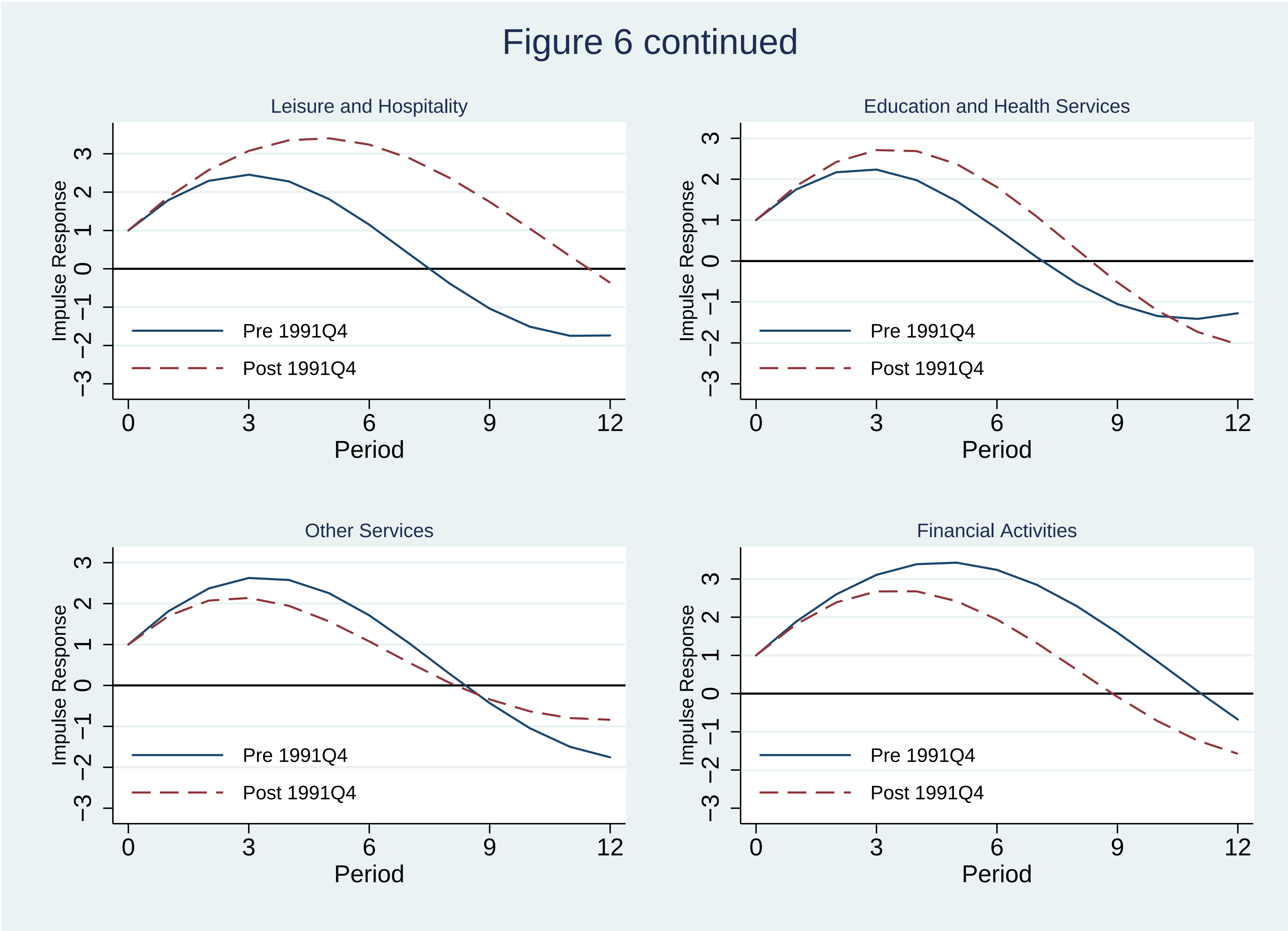
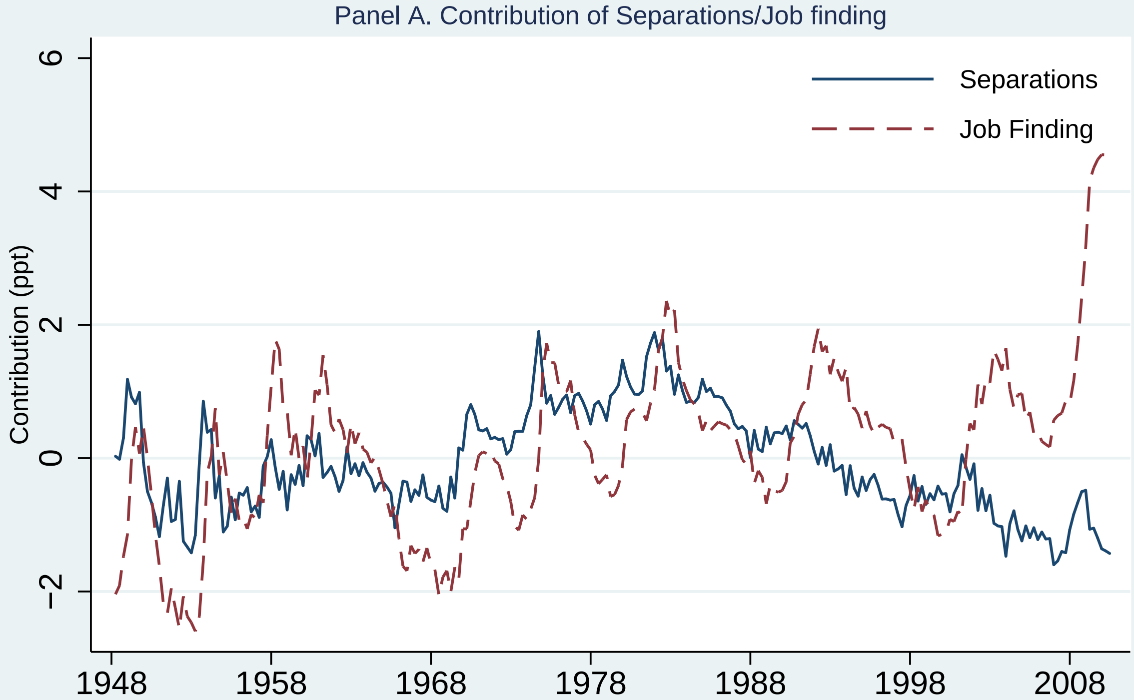


Figure 6 continued
Leisure and Hospitality
Education and Health Services
Other Services
Financial Activities
Impulse Response
Period
Pre 1991Q4
Post 1991Q4
−3 −2 −1 0 1 2 3
0 3 6 9 12

Figure 7. Separation and Job Finding



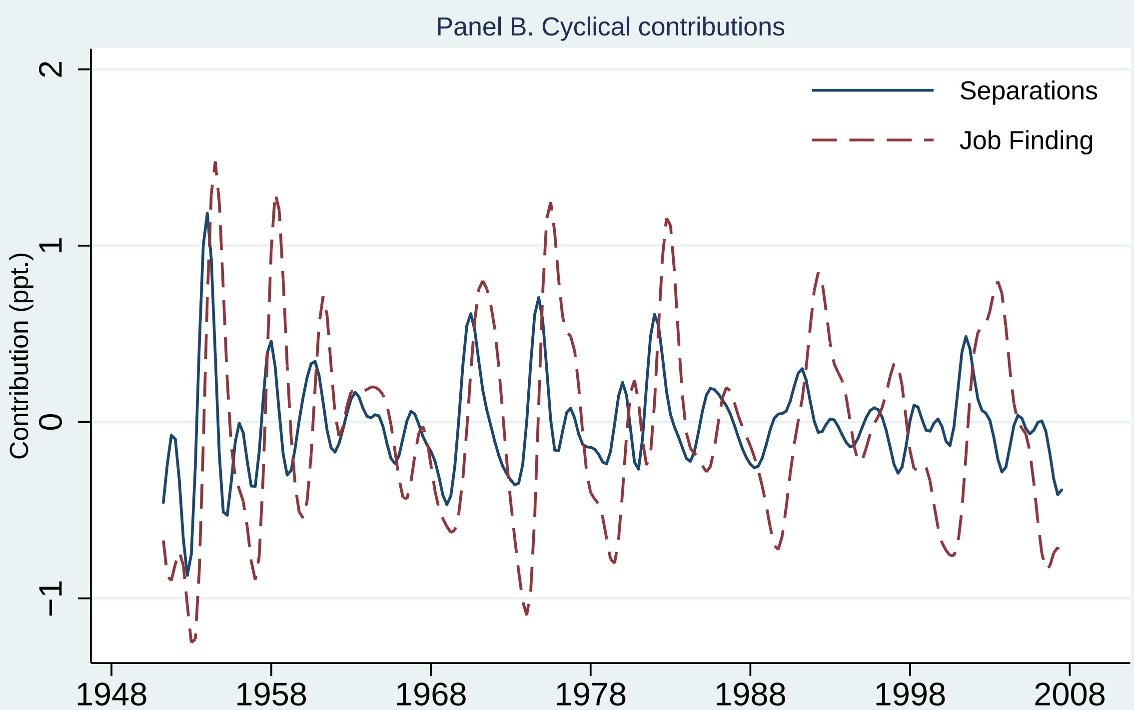
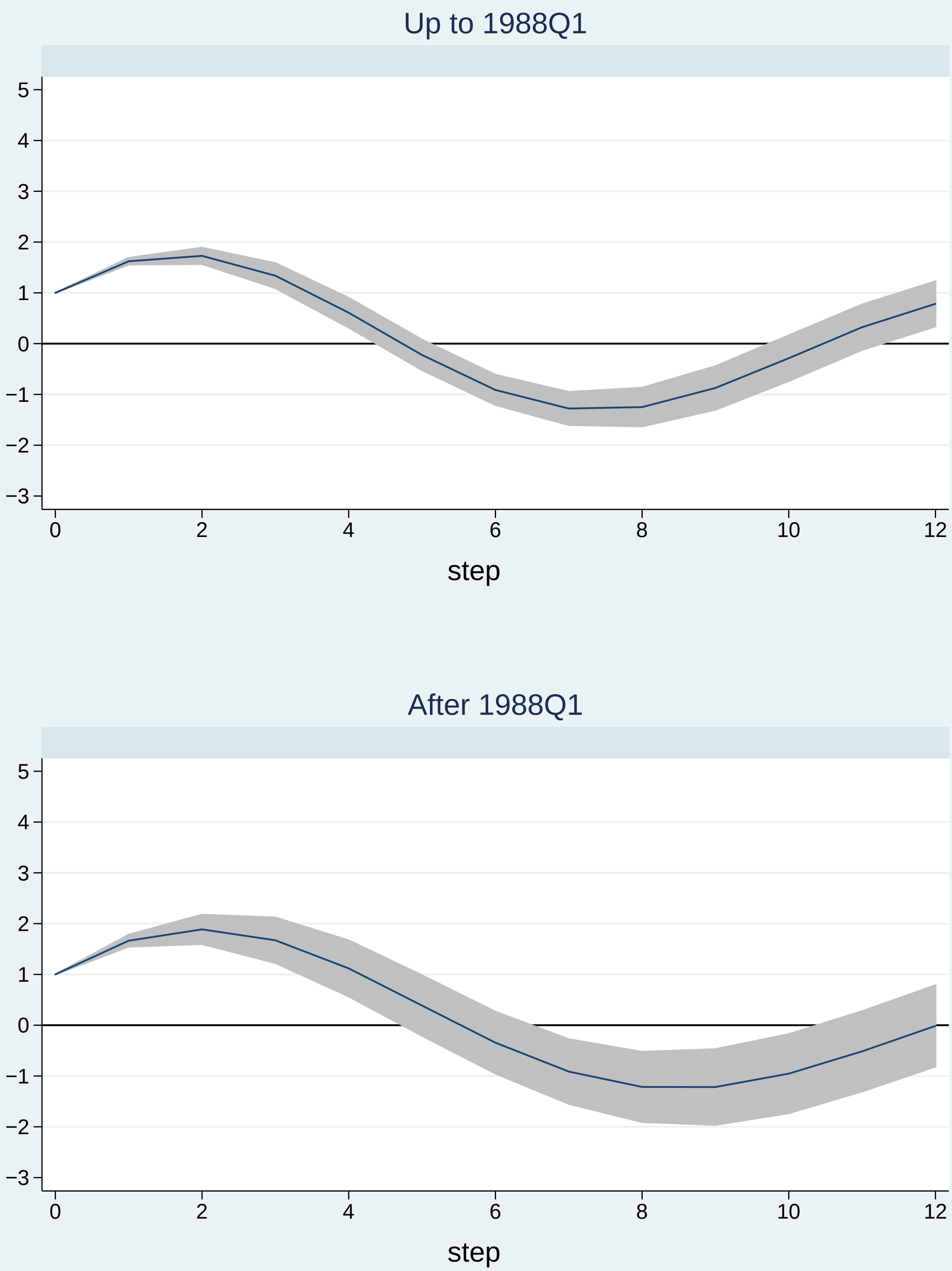
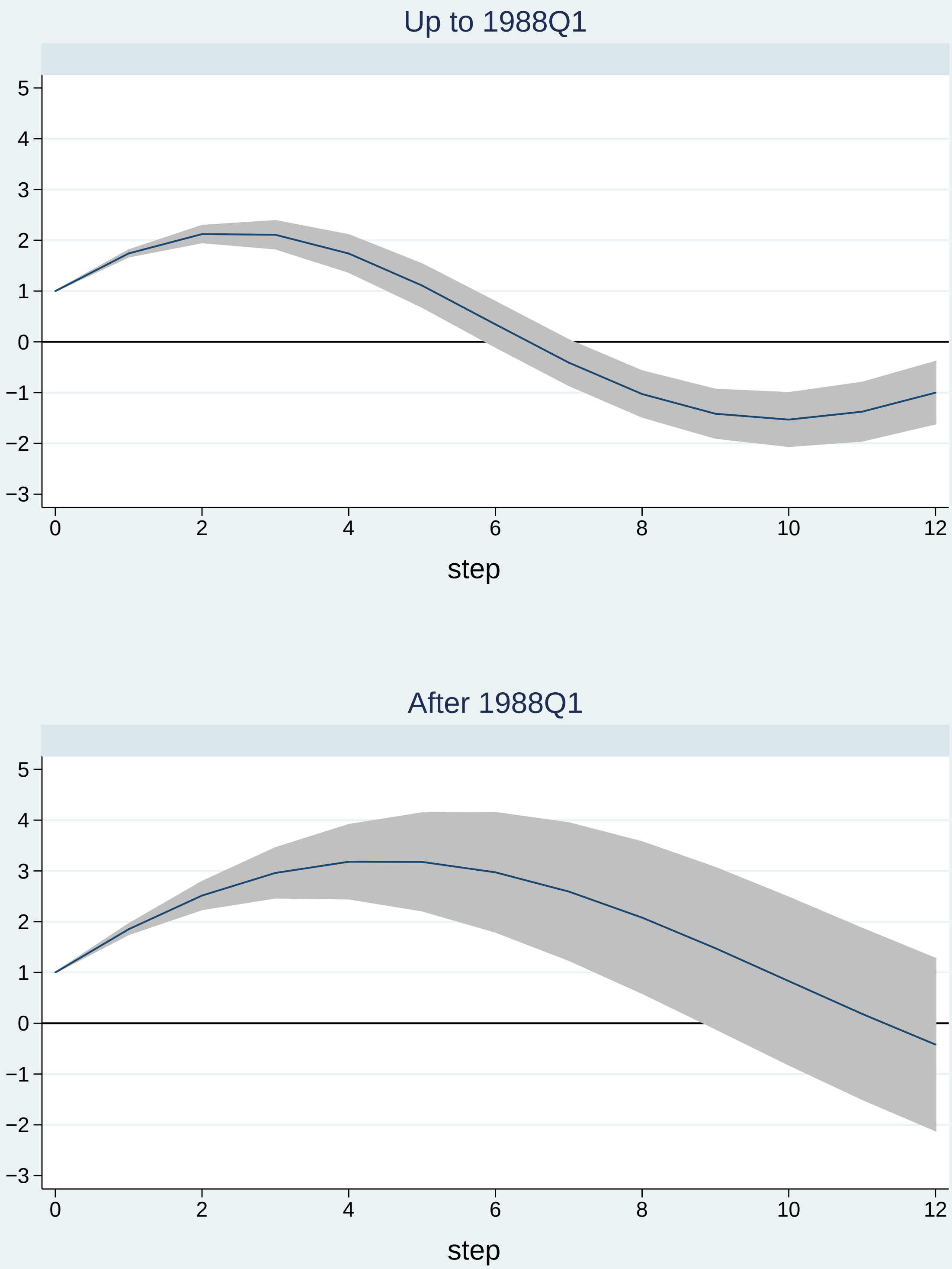


Figure 8. Impulse Responses of Separations Contribution



Gray−shaded regions contain 95 percent confidence intervals.

Figure 9. Impulse Responses of Job Finding Contribution



Gray−shaded regions contain 95 percent confidence intervals.

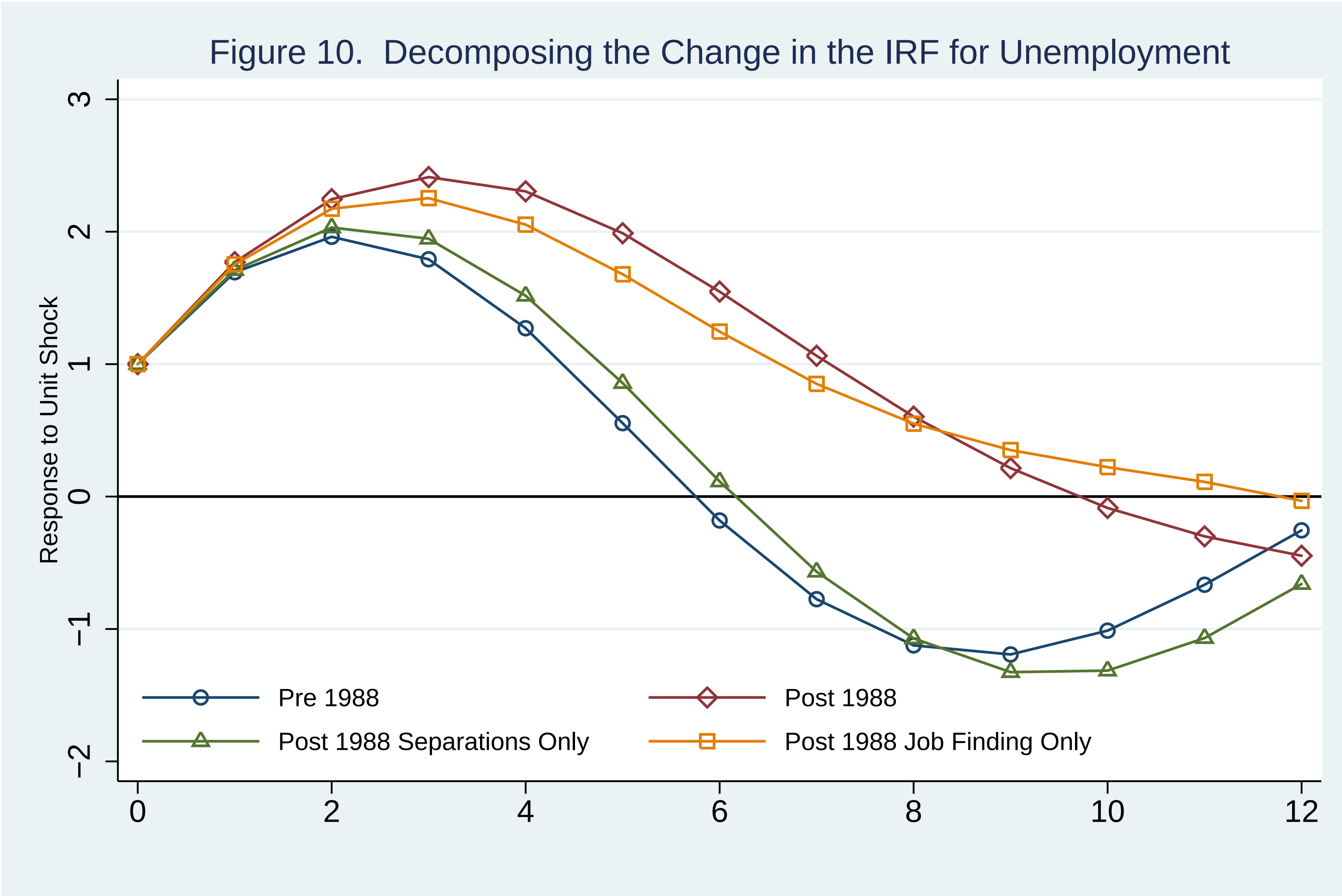
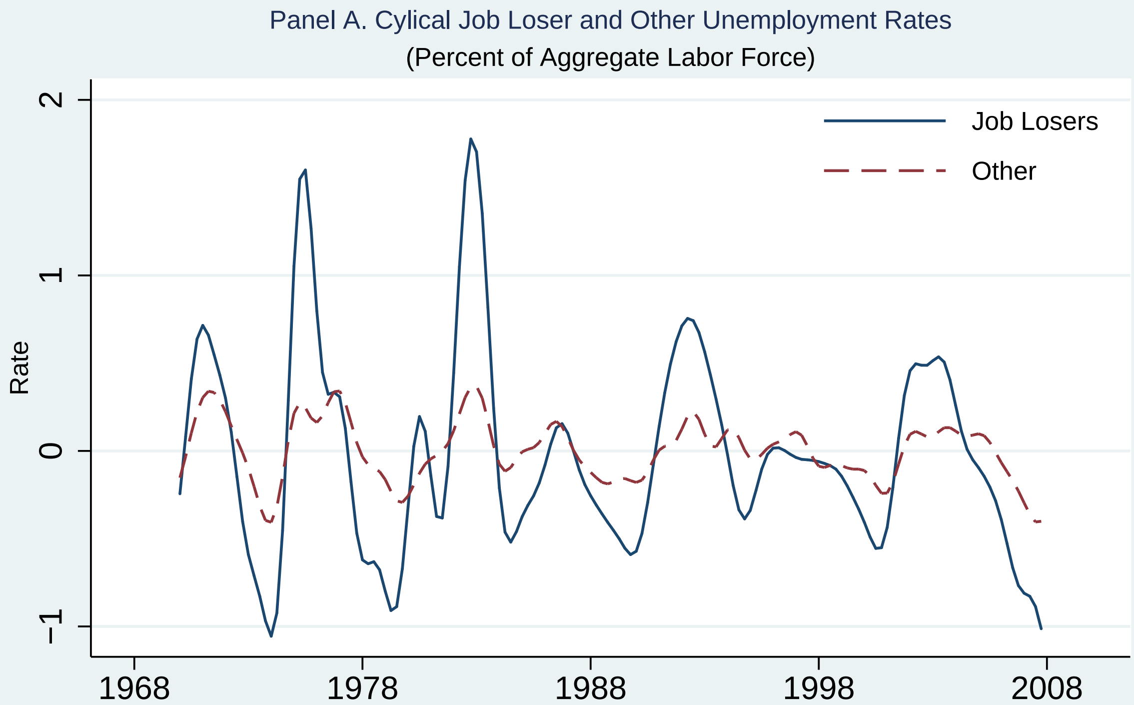


Figure 10. Decomposing the Change in the IRF for Unemployment
Response to Unit Shock
3
2
1
0
−1
−2
0
2
4
6
8
10
12
Pre 1988
Post 1988
Post 1988 Separations Only
Post 1988 Job Finding Only

Figure 11. Unemployment by Reason



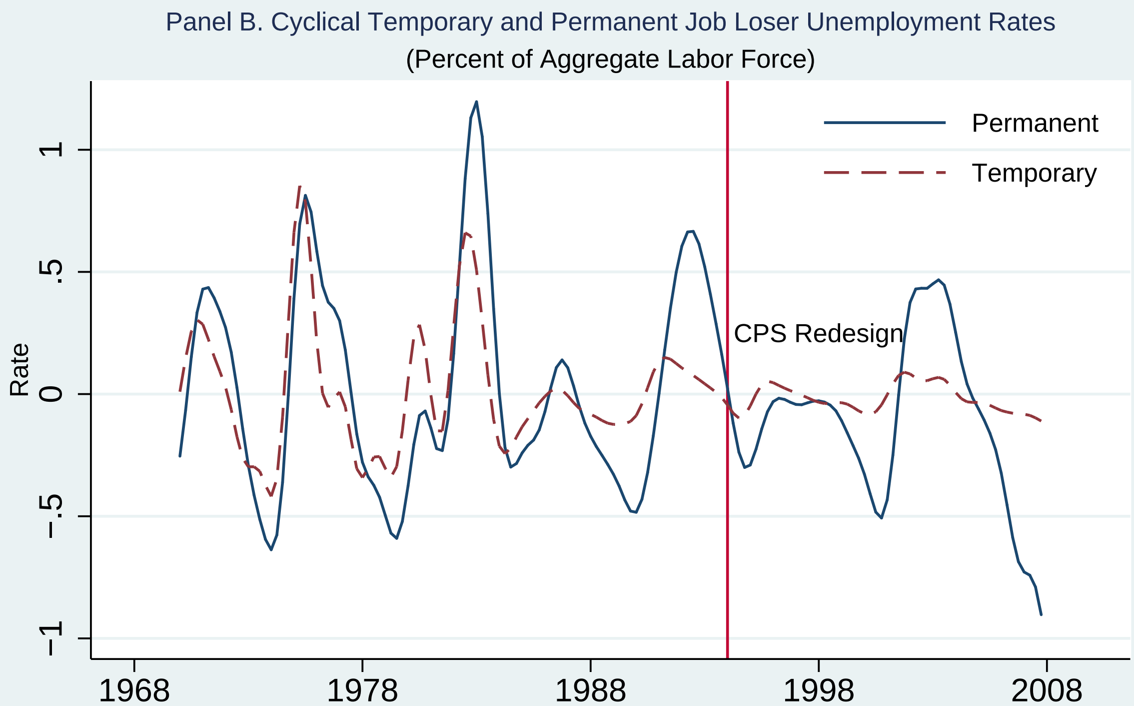
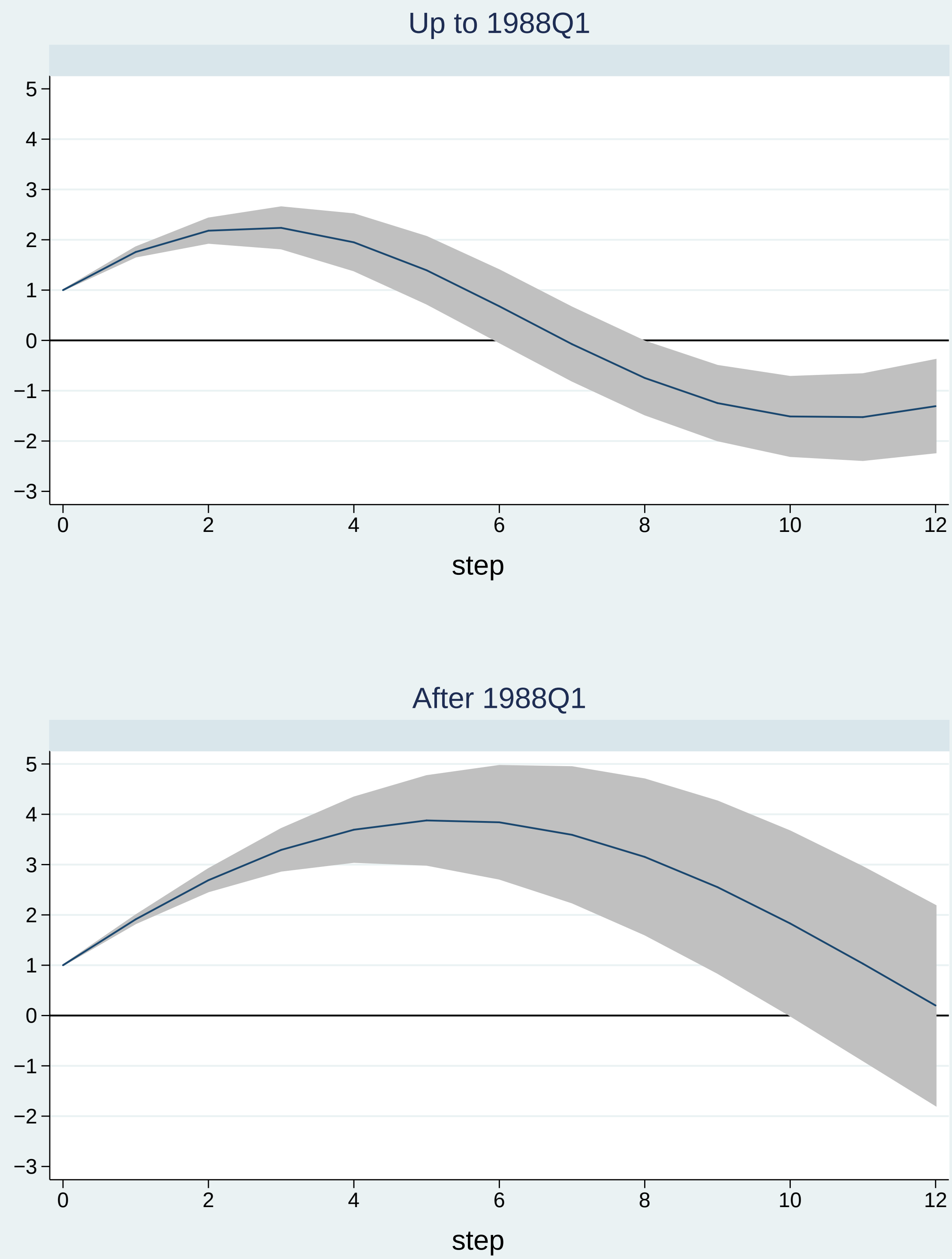
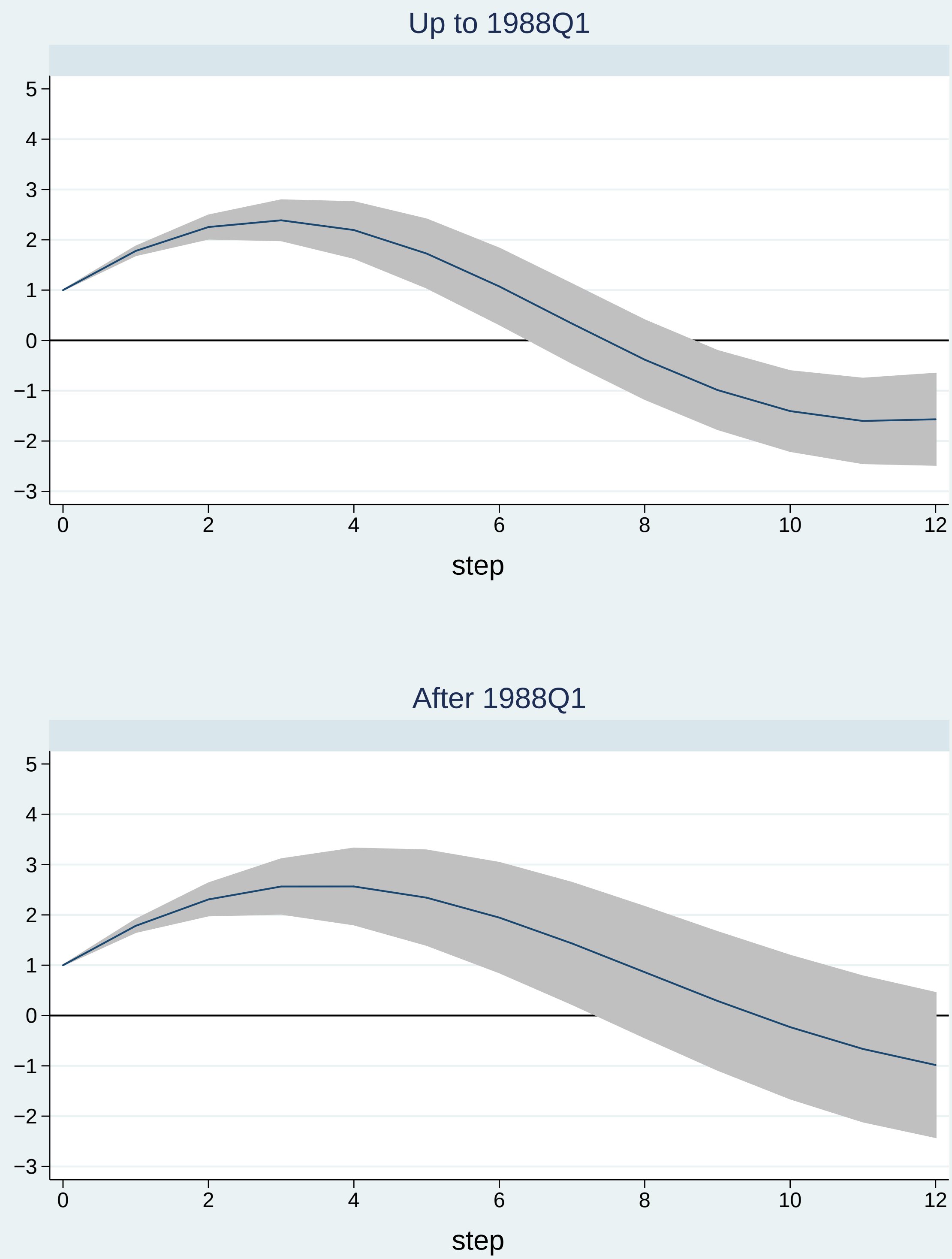


Figure 12. Impulse Responses of Job Loser Unemployment



Gray−shaded regions contain 95 percent confidence intervals.

Figure 13. Impulse Responses of Other Unemployment



Gray−shaded regions contain 95 percent confidence intervals.

Figure 14. Decomposing the Change in the IRF for Unemployment

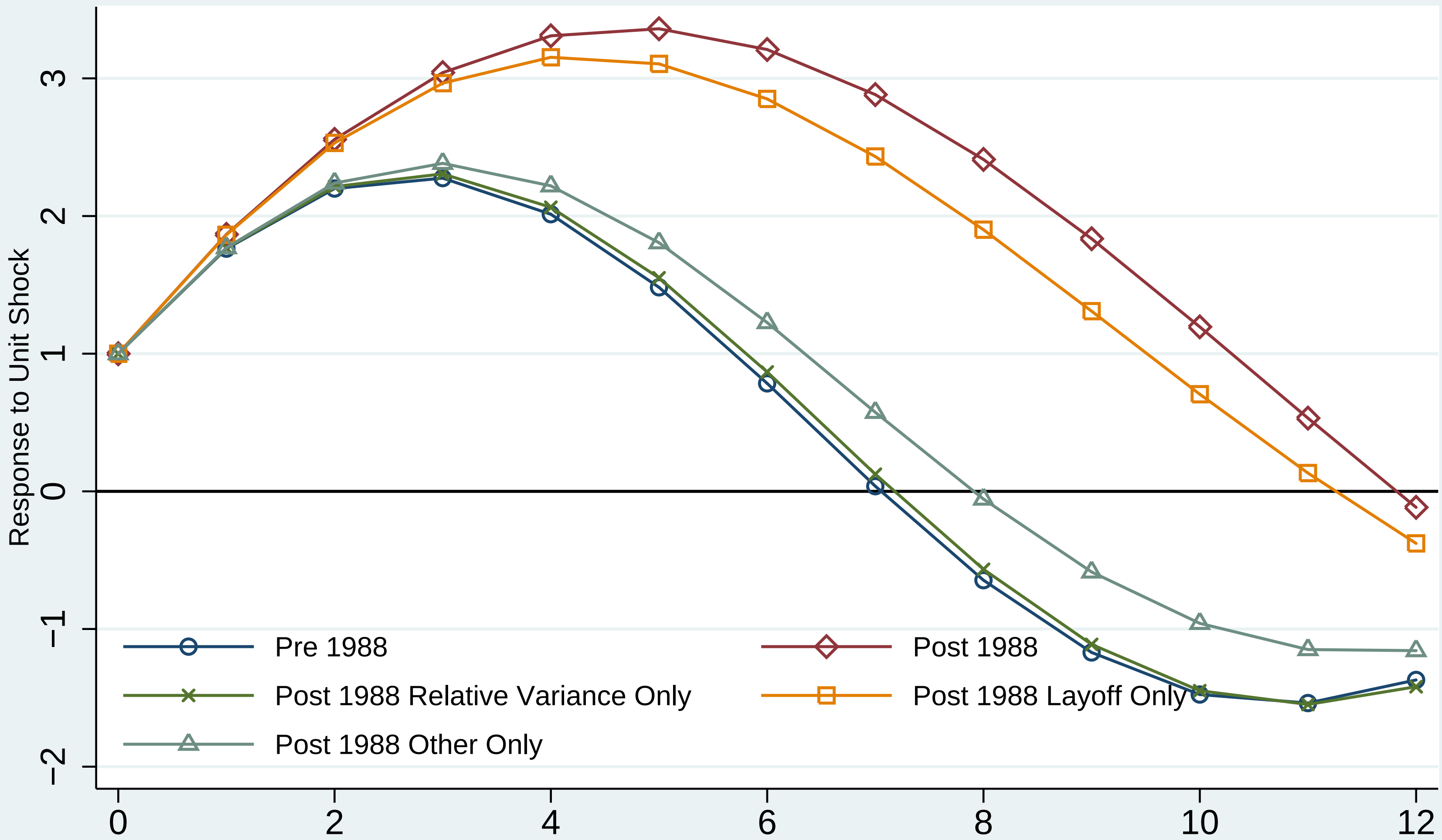


Figure 15. Average Duration of Temporary Layoff Unemployment

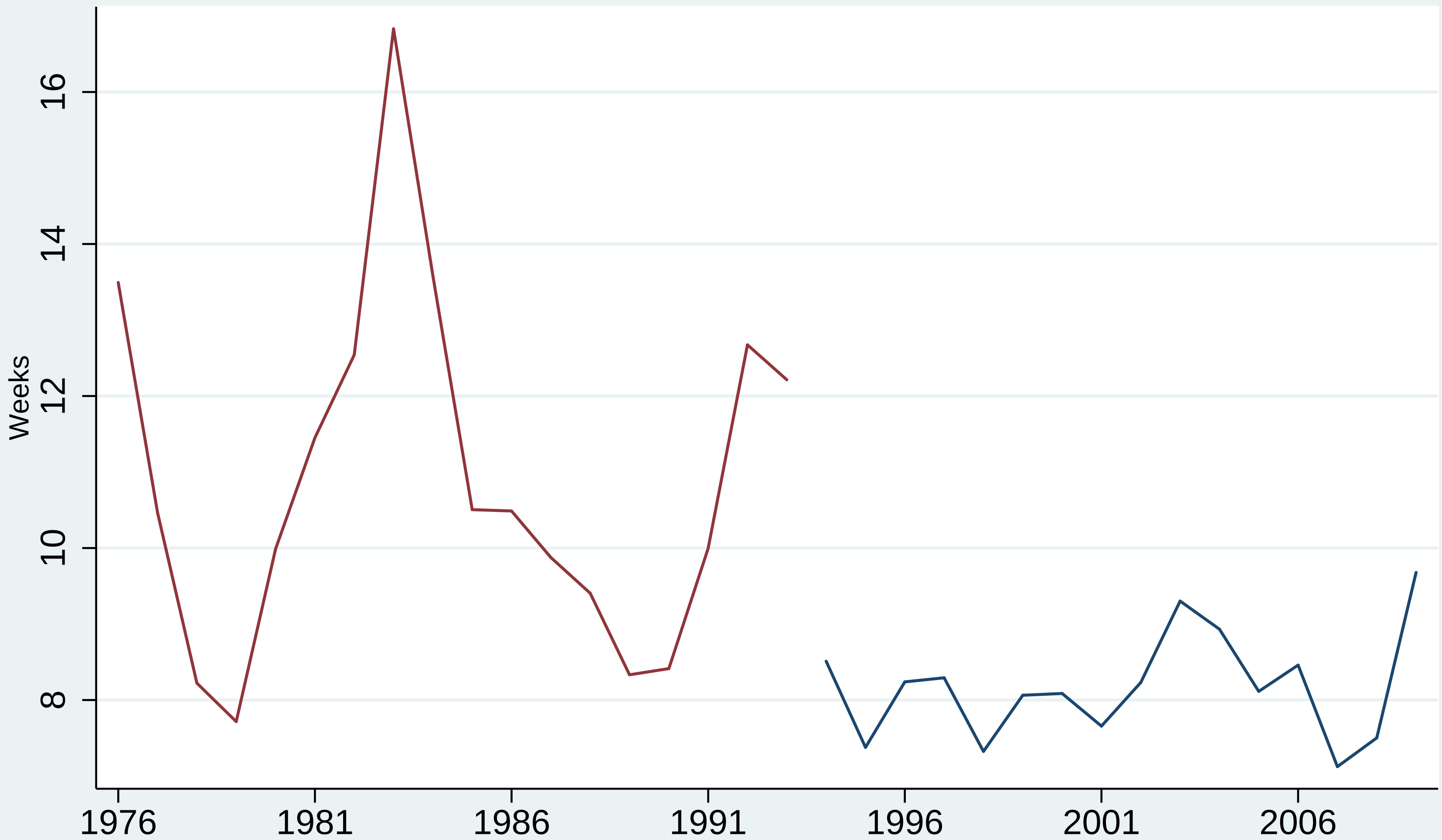


Figure 16. Missclassification Share

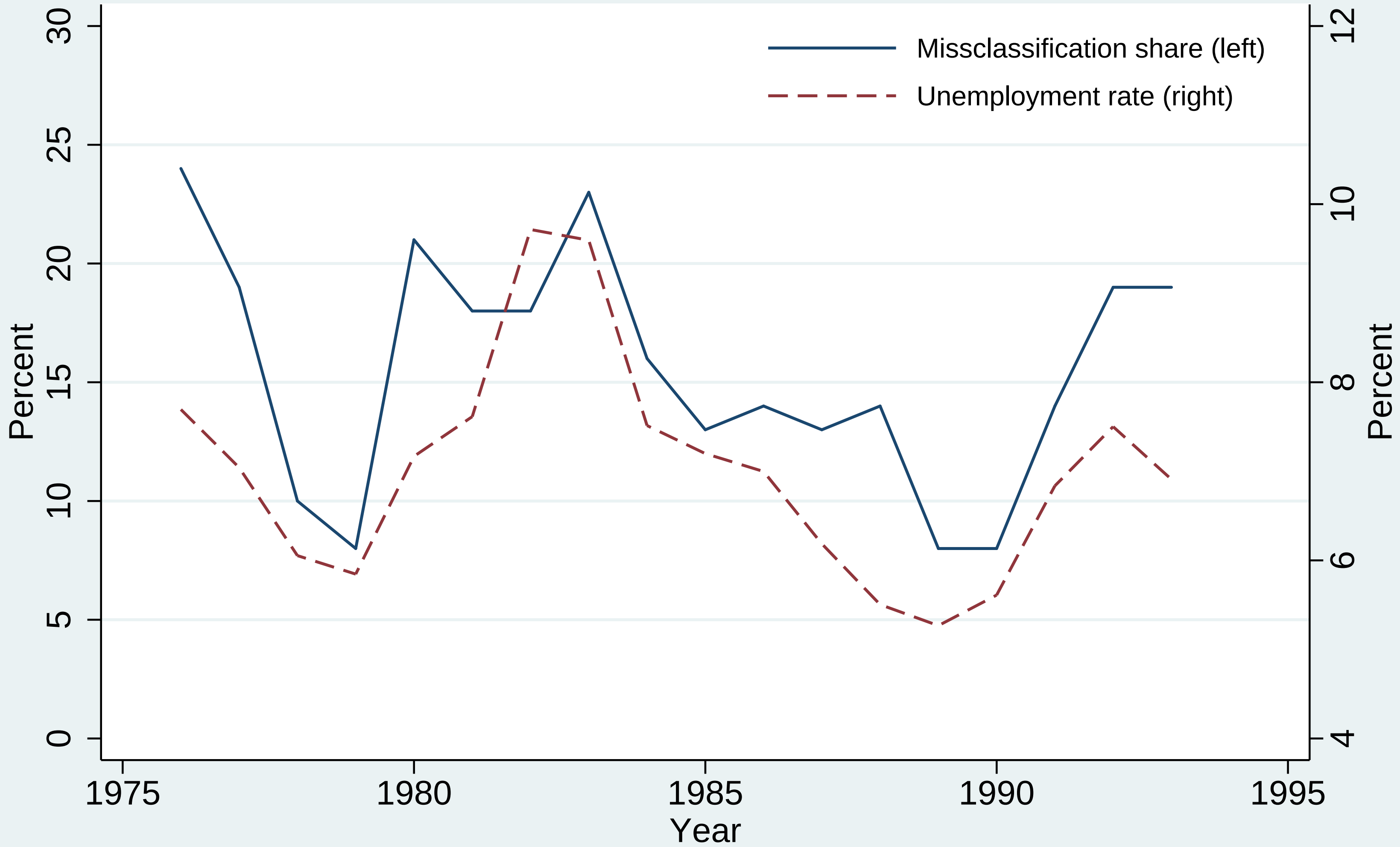


Figure 17. Layoff Unemployment Adjusted for Missclassification

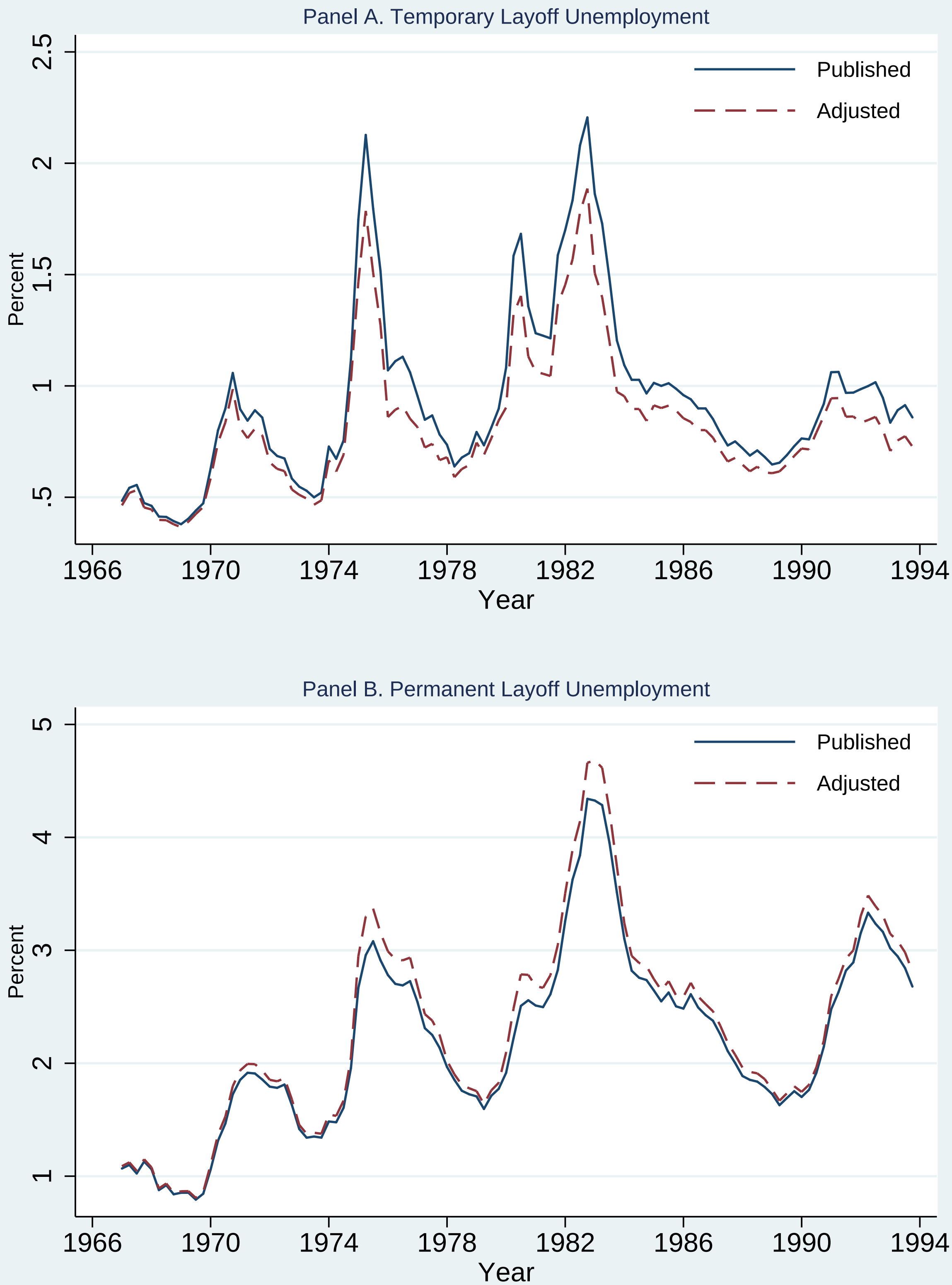
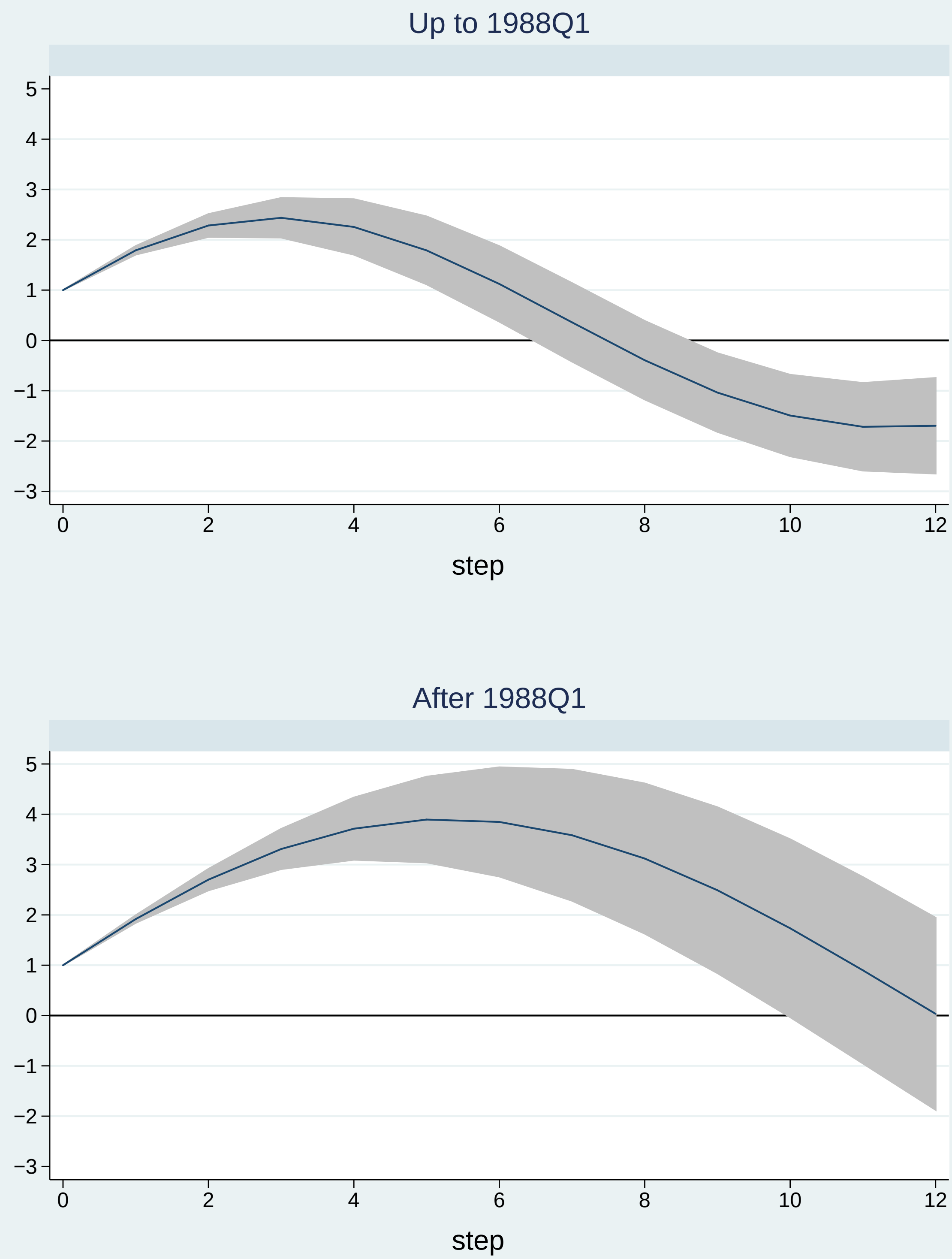
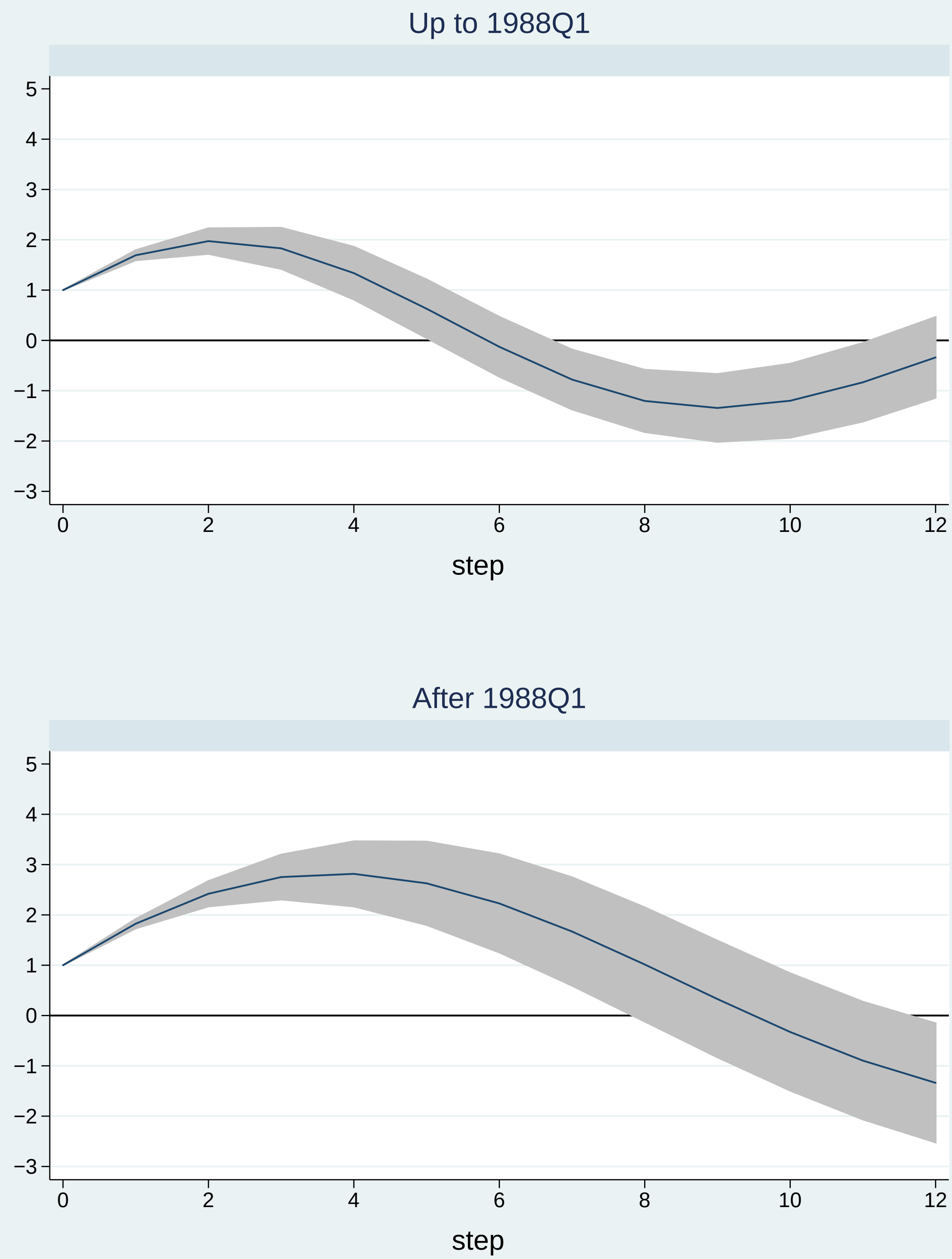


Figure 18. Impulse Responses of Adjusted Permanent Layoff Unemployment



Gray−shaded regions contain 95 percent confidence intervals.

Figure 19. Impulse Responses of Adjusted Temporary Layoff Unemployment



Gray−shaded regions contain 95 percent confidence intervals.

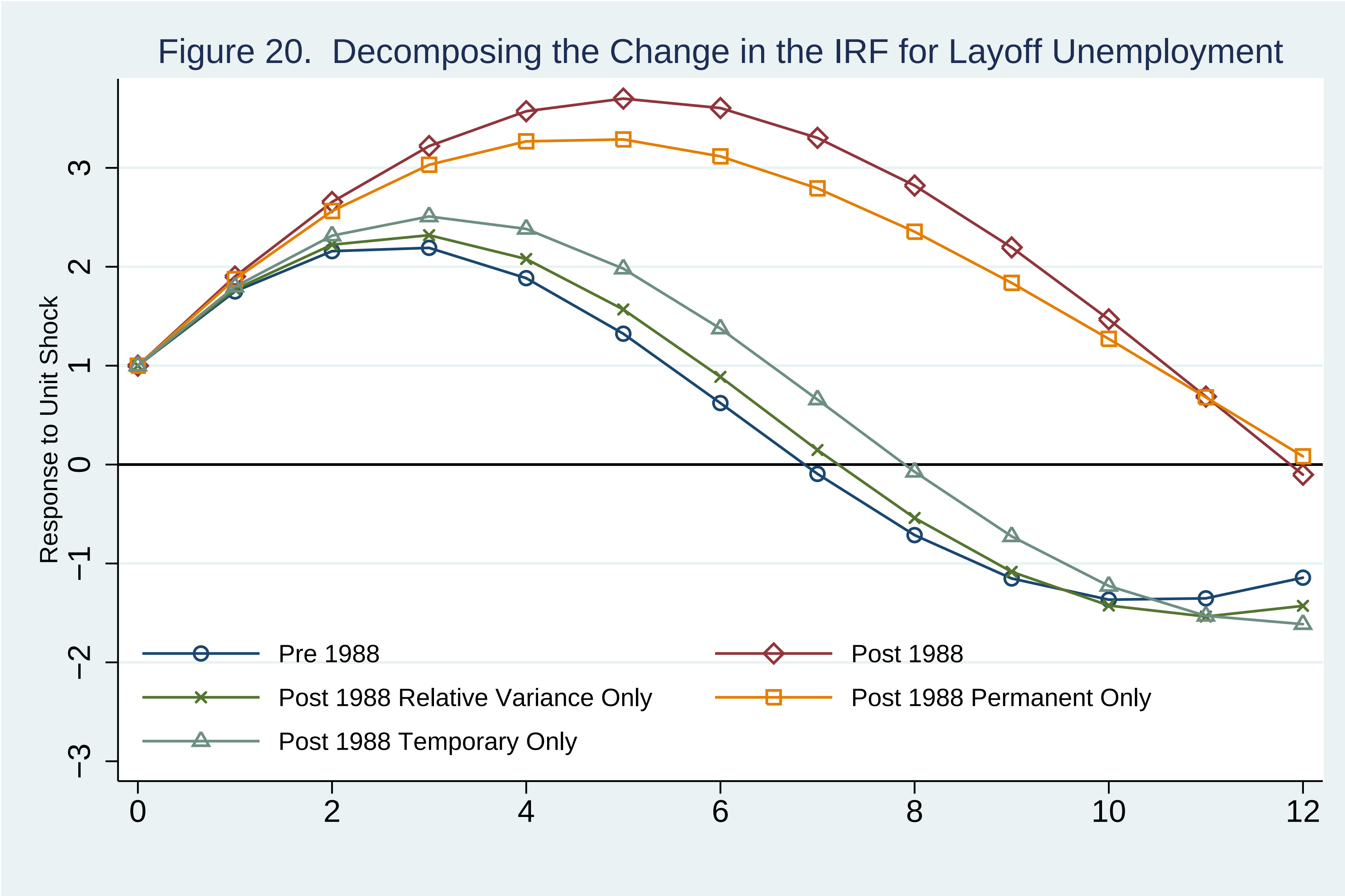


Figure 20. Decomposing the Change in the IRF for Layoff Unemployment
Response to Unit Shock
3
2
1
0
−1
−2
−3
0
2
4
6
8
10
12
Pre 1988
Post 1988
Post 1988 Relative Variance Only
Post 1988 Permanent Only
Post 1988 Temporary Only