A Comparison of Business Cycle Regime Nowcasting Performance between Real-time and Revised Data

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Markov-switching models used for 'nowcasting' business cycle regimes are based on real-time data and recursive estimation of the parameters of the model. Similar estimation based on the revised data and recursively estimated parameters can provide quite different inference about the current regime. This paper examines how much the nowcasting inference changes between real-time data and revised data in univariate and bivariate models. Univariate models comparing the real-time data and revised data of US GDP show sizeable difference in inference about the current regime. However, the difference subtiantially reduces in bivariate common regime model using industrial production along with the GDP data. The estimates also show a similar reduction of difference in inference using payroll employment data. These results suggest that the uncertainty about the current unobserved regime due to data revisions can be reduced by using multivariate models with a common underlying regime.

Keywords: Regime-switching models, business cycle, nowcasting, real-time data.

JEL Codes: C32, E32.

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1. Introduction

The process of classifying business cycle regimes into either an expansion phase or a recession phase in real time is a challenging task in empirical business cycle literature. It involves three separate elements: the selection of the model to be used, the use of real time data and the recursive estimation of model parameters. On the first issue, the regime switching models, introduced by Hamilton (1989, 1990), perform quite well in classifying and 'nowcasting' economic activity between expansion and recession phases[1]. Further research extended these models in multiple directions to analyze the business cycle features. One of them was to use multiple indicators for estimation of the business cycle phases. Extending Stock and Watson's (1989, 1991) models of coincident indicators, Chauvet (1998), Kim and Nelson (1998) construct dynamic factor models in the regime switching context.

The second element is the issue of real-time data put forward by Croushore and Stark (2001, 2003). Macroeconomic data used for business cycle estimation is revised multiple times later on. Arouba (2008) shows such revisions are large and do not average to zero. As a result, as Orphanides and van Norden (2002) show, business cycle measures based on data available at the time could be quite different from business cycle measures based on the revised data. Orphanides (2001) show that monetary policy based on real time data can differ substantially from one that uses revised data. Finally, the element of recursive (or rolling) estimation of the model parameters in the regime switching context was used by Layton (1996) with revised data. Recently, Chauvet and Hamilton (2006), Chauvet and Piger (2008) use dynamic regime-

[1] The term 'nowcasting' implies, in the regime-switching context, inference about the unobserved regime in the last period based on currently available data.

switching factor models based on real time data to compare business cycle dating that use recursive estimation of the model parameters[2].

This paper examines how much the nowcasting inference changes between real-time data and revised data in univariate and bivariate models. Univariate models comparing the real-time data and revised data of US GDP show sizeable difference in inference about the current regime. However, in the bivariate common regime models using either industrial production or payroll employment along with the GDP data, the difference in inference about the current regime due to data revisions reduces substantially. The results suggest that the uncertainty about the current unobserved regime due to data revisions can be reduced by using multivariate models with a common underlying regime.

The benchmark bivariate model is presented, estimated and analyzed in section 2 along with the data description and the results from a modified bivariate model. Summary of the results and conclusions are in section 3.

2. The Bivariate Regime Switching Model

2a. The Bivariate Markov Switching Model

The bivariate regime switching model of the business cycles uses two observed variables, y_1 and y_2, to draw inferences about business cycle regimes. Following Chauvet and Piger (2003), Nalewaik (2007), the primary variable is real GDP growth, y_1, which varies due to a switching unobserved business cycle state, S_t and a white noise component $\varepsilon_{1,t}$. The variable S_t can take the value zero in expansion or one in recession. Similarly, the industrial production

[2] There are many other studies that extended the regime switching models in different directions or used real time data for macroeconomic analysis. Hamilton (2005) provides a detailed description of other studies on the regime-switching topic. Croushore (2008) provides an extensive review of the real-time data studies.

growth, y_2, is also driven by the unobserved business cycle state S_t and another white noise component $\varepsilon_{2,t}$.

1. $y_{1,t} = \mu_0(1-S_t) + \mu_1 S_t + \varepsilon_{1,t}$; $S_t = 0, 1$; $t = 1, 2, \ldots, T$.

2. $y_{2,t} = \gamma_0(1-S_t) + \gamma_1 S_t + \varepsilon_{2,t}$

Following Nalewaik (2007), the noise components of the two variables are allowed to be correlated; $Corr(\varepsilon_{1,t}, \varepsilon_{2,t}) = \rho_{12}$. We also assume $\varepsilon_{1,t} \sim N(0, \sigma_1^2)$ and $\varepsilon_{2,t} \sim N(0, \sigma_2^2)$.

The unobserved business cycle states are assumed to follow a Markov process of order one with constant transition probabilities p_{00} and p_{11}:

$$\Pr ob[S_t = 0 \mid S_{t-1} = 0] = p_{00} \text{ and } \Pr ob[S_t = 1 \mid S_{t-1} = 1] = p_{11}.$$

The one-sided filtered probability of recession and expansion is denoted by P_t and $1-P_t$ respectively; $\Pr ob[S_t = 1 \mid \Omega_t] = P_t$. Finally, in regime switching models the true nowcasted probabilities of the states are only estimated in the last observation of each vintage of data, T, when both the estimated parameters and the filtered probabilities are based on the same data. Therefore, the probability of nowcasted NBER announced state at time T, denoted as P, can be specified as:

$$P = I_T * (P_T) + (1 - P_T) * (1 - I_T)$$

where I_T denotes the NBER announced state at time T and P_T denotes the one sided filtered probability of recession at time T.

2b. The Data and the Estimation

The real GDP and payroll employment data used are quarterly time series, ranging from 1959:4 to 2008:1, obtained from real time data archive of the Federal Reserve Bank of

Philadelphia. The industrial production data used are from 1969:4 to 2008:1. Each vintage of the GDP data represents data availability as of middle of the next quarter[3]. Although the payroll employment and industrial production data are available monthly; to make it consistent with the quarterly frequency of GDP the quarterly averages of each series are used based on the vintage of middle month of the next quarter[4]. Figure 1 shows an example of how each data series in quarter one of 1990 was subsequently revised multiple times. All the indicators used in the estimation of the models are in quarterly growth rates.

The selection of industrial production and payroll employment as additional indicators beyond GDP is driven by their use in past studies like Chauvet (1998), Chauvet and Piger (2008). They are also mentioned as important business cycle indicators by the NBER business cycle dating committee. Moreover, these variables are widely available for other countries thereby making it easier to compare results. The univariate and bivariate regime switching models are estimated using maximum likelihood procedure. The filtered estimates of the probabilities of each regime are then computed for nowcasting of the business cycle regimes. However, only the filtered probabilities for the last observation will show the true nowcasted probabilities that use the same sample for both maximum likelihood estimation of the parameters and the filtered probabilities. So, the estimation is done recursively, as in Layton (1996) and Chauvet and Piger (2008), for each vintage.

2c. Performance of GDP and industrial production data

[3] The vintage of 1996Q1 does not have the data on 1995Q4 due to shutdown of the government. It is reported as a part of 1996Q2 vintage. We assume in recursive estimation of the model that the 1995Q4 data as reported in 1996Q2 was available in 1996Q1.

[4] The industrial production data vintages of 1998, February, May and August do not have data for 1969. However, the data for 1970Q1-Q4 is unchanged between 1997 vintages and 1998 vintages. So, we assumed the 1997 vintage of 1969 data to be true for 1998 vintage as well.

The empirical analysis starts out by estimating the univariate regime switching model of real-time GDP growth for the samples 1969:2 –1989:4 to 1969:2 – 2008:1[5, 6]. The sample selection is driven by availability of the real time industrial production data throughout the sample. This makes it easier to compare the empirical performance of the bivariate specifications. The results are reported in panel A of table 1. The numbers reported are the average estimates of parameters for the 74 samples with end dates ranging from 1989:4 to 2008:1. The average estimate of standard deviation of the noise component is 0.74. It also shows, as expected, a positive average estimate for μ_0 and a negative average estimate for μ_1. Finally, P_U is the average probability of correctly nowcasted NBER reported states in the univariate model. It shows that the univariate model correctly nowcasts the NBER regimes, both expansions and recessions, with an average probability of 83 percent using real-time data.

The same recursive estimation of the univariate model is repeated using the revised real GDP data of 2008 second quarter vintage and reported in panel B of table 1. The average parameter estimates are largely similar to that of panel A. The mean absolute deviation between the nowcasted recession probabilities using real-time and the nowcasted recession probabilities using revised data is about 10 percent. The nowcasted recession probabilities from both the real time data estimation and revised data estimation are illustrated in the top panel of figure 2. Both of them capture the 1990-91 recession and 2001 recession reasonably well.

[5] The model assumes that the GDP growth data is serially uncorrelated after allowing for the business cycle regimes, as in Chauvet and Piger (2003), Nalewaik (2007). A simple regression of the GDP growth data on a constant, a dummy for the NBER recessions and lagged GDP growth yielded a small and statistically insignificant coefficient of -0.02 on the lagged GDP growth.

[6] An additional issue that is not addressed in this paper due to space consideration is to account for the great moderation as discussed in Kim and Nelson (1999) and McConnell and Perez-Quiros (2000). Allowing for a break in the variance of the shocks in 1984:1 does not change the results of this paper qualitatively.

The estimation results of the bivariate model with GDP growth and industrial production growth based on real-time data and revised data are reported in panel C and D respectively of table 1. The average estimate of the standard deviation of the noise component of industrial production growth is approximately 1.2 in both cases, more volatile than real GDP growth. The average correlation estimate between the noise components is about 0.65 for both real-time data and revised data. The estimates also show, as expected, a positive average estimate for γ_0 and a negative average estimate for γ_1. Finally, P_B is the average probability of correctly nowcasted NBER reported states in the bivariate model. It shows that the bivariate model correctly nowcasts the NBER regimes with an average probability of 91 to 94 percent.

The nowcasted recession probabilities from both the real time data estimation and revised data estimation from the bivariate model are illustrated in the bottom panel of figure 2. Both of them capture the 1990-91 recession and 2001 recession reasonably well. However, they do not pick up the 2008 recession yet, a result similar to Chauvet and Piger (2008) study suggesting business cycle peaks are harder to capture in real time than business cycle troughs. Even a casual look at the graph suggests that the nowcasted recession probabilities in the bivariate model for both types of data are more similar to each other than was the case in the univariate model. Quantitatively, the mean absolute deviation between the nowcasted recession probabilities using real-time and the nowcasted recession probabilities using revised data is about 4 percent, two-fifths of the mean absolute deviation in the univariate case. This result shows that the difference in nowcasting inference between real-time data and revised data can be reduced by using multiple indicators of business cycle[7].

[7] Chauvet and Piger (2008) mentioned that revised data did not change the business cycle dates obtained using real-time data. However, they did not directly compare the nowcasted regime probabilties between univriate and mulitivariate models.

2d. Performance of GDP and payroll employment data

This section examines the performance of another commonly used measure, payroll employment, in understanding business cycle regimes. To model the labor market variables with real GDP data for estimating business cycle regimes one needs to modify equation (2). There are three potential issues in modeling the labor market and output beyond a simple Okun's Law. One, previous studies like Clark (1989) suggest that the labor market responds sluggishly to the output market. Two, Silvapulle et al. (2004) suggest asymmetric response of labor market to cyclical output. Three, the Stock and Watson (2005) study shows a fair amount of independent variation in the labor market beyond the output volatility. Based on the above three issues, equation (2) can be modified to allow for the sluggish labor market adjustment and built-in asymmetric response to economic states[8]:

3. $$y_{2,t} = \gamma_0(1 - S_t) + \gamma_1 S_t + \phi\left(y_{2,t-1} - \gamma_0(1 - S_{t-1}) - \gamma_1 S_{t-1}\right) + \varepsilon_{2,t}$$

where ϕ is the coefficient of first order autoregression. Equations (1) and (3) will now constitute the new bivariate model of real GDP growth and payroll employment growth.

The recursive estimations of the univariate regime switching model of real-time GDP growth and bivariate regime switching model of real-time GDP growth and payroll employment growth are based on the samples 1959:4 –1984:4 to 1959:4 – 2008:1. The univariate real-time data results are reported in panel A of table 2 and the univariate revised data results are in panel B of table 2. The numbers reported are the average estimates of parameters for the 94 samples with end dates ranging from 1984:4 to 2008:1. They show 0.74 as the average estimate of standard deviation of the noise component in both panels, similar to estimates in table 1. They

[8] Simple full sample regressions of payroll employment growth on a constant, dummy for NBER announced recessions and lagged payroll employment growth show, unlike the output variables, a fair amount of serial correlation that can be adequately accounted for by the AR(1) framework. Likelihood ratio tests for AR(2) or richer dynamics were statistically insignificant.

also show positive average estimates for μ_0 and negative average estimates for μ_1. Finally, P_U, the average probability of correctly nowcasted NBER reported states in the univariate model shows the average probability of 85 percent using both real-time data and revised data. The mean absolute deviation between the nowcasted recession probabilities using real-time and the nowcasted recession probabilities using revised data is about 8 percent.

The estimation results of the bivariate model with GDP growth and payroll employment growth based on real-time data and revised data are reported in panel C and D respectively of table 2. The average estimate of the standard deviation of the noise component of payroll employment growth is approximately 0.25 in both cases, less volatile than real GDP growth. The average correlation estimate between the noise components is about 0.61 for both real-time data and revised data. The estimates also show a positive average estimate for γ_0 and a negative average estimate for γ_1 in both panels. Finally, P_B, the average probability of correctly nowcasted NBER reported states in the bivariate model shows that the bivariate model correctly nowcasts the NBER regimes with an average probability of 84 to 86 percent.

The nowcasted recession probabilities from both the real time data estimation and revised data estimation from the univariate model are illustrated in the top panel of figure 3. The nowcasted recession probabilities from both the real time data estimation and revised data estimation from the bivariate model are illustrated in the bottom panel of figure 3. The visual comparison of the real time nowcasting inference and revised data nowcasting inference between the two panels is less clear than in figure 2. The mean absolute deviation between the nowcasted recession probabilities using real-time and the nowcasted recession probabilities using revised data is about 6 percent in the bivariate model, smaller than the 8 percent mean absolute deviation in the univariate case. Overall, the estimates of this section supports the empirical result that the

difference in nowcasting inference between real-time data and revised data can be reduced by using multiple indicators of business cycle, although the magnitude of reduction will depend on the selection of the specific indicators.

3. Conclusion

To conclude, this paper compares changes in nowcasting inference between the real-time data and the revised data in univariate and bivariate models. Univariate models comparing the real-time data and the revised data of US GDP show sizeable differences in inference about the current regime. However, the difference subtiantially reduces in bivariate common regime model using industrial production along with the GDP data. The estimates also show a similar reduction of difference in inference using payroll employment data. These results suggest that the uncertainty about the current unobserved regime due to data revisions can be reduced by using multivariate models with a common underlying regime.

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References:

Aruoba, S. Boragan, (2008), "Data Revisions Are Not Well Behaved." *Journal of Money, Credit, and Banking*, 40 (2-3), 319 -340.

Chauvet, M., (1998), "An Econometric Characterization of Business Cycle Dynamics with Factor Structure and Regime Switching", *International Economic Review*, 39, 969-996.

Chauvet, M. and J. Piger, (2003), "Identifying Business Cycle Turning Points in Real Time", *Federal Reserve Bank of St. Louis Review*, 85, 47-61.

Chauvet, M. and J. Hamilton, (2006), "Dating Business Cycle Turning Points", in *Nonlinear Analysis of Business Cycles*, edited by Costas Milas, Philip Rothman, and Dick van Dijk, Elsevier.

Chauvet, M. and J. Piger, (2008), "A Comparison of the Real-Time Performance of Business Cycle Dating Methods", *Journal of Business and Economic Statistics*, 26, 42-49.

Croushore, Dean, and Tom Stark, (2001) "A Real-Time Data Set for Macroeconomists," *Journal of Econometrics* 105, 111–130.

Croushore, Dean, and Tom Stark, (2003), "A Real-Time Data Set for Macroeconomists: Does the Data Vintage Matter?" *Review of Economics and Statistics* 85, 605–617.

Croushore, Dean (2008), "Frontiers of Real-time Data Analysis", Federal Reserve Bank of Philadelphia, manuscript.

Clark, Peter K., (1989), "Trend Reversion in Real Output and Unemployment", *Journal of Econometrics*, 40, 15-32.

Hamilton, J.D., (1989), "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle", *Econometrica*, 57, 357-384.

Hamilton, J. D., (1990), "Analysis of Time Series Subject to Changes in Regime", *Journal of Econometrics*, 45, 39-70.

Hamilton, J. D., (2005), "Regime Switching Models", *New Palgrave Dictionary of Economics*, forthcoming.

Kim, C. J., Morley, J. and J. Piger, (2005), "Nonlinearity and the Permanent Effect of Recessions", *Journal of Applied Econometrics*, 20, 291-309.

Kim, C. J. and C. R. Nelson, (1998), "Business Cycle Turning Points, a New Coincident Index, and Tests of Duration Dependence Based on a Dynamic Factor Model with Regime Switching", *The Review of Economics and Statistics*, 80, 188-201.

Kim, C. J. and C. R. Nelson, (1999), "Has the US economy become more stable? A Bayesian approach based on a Markov-Switching model of the business cycle", *The Review of Economics and Statistics*, 81, 608-616.

Laubach, Thomas (2001), "Measuring the NAIRU: Evidence from Seven Economies", *The Review of Economics and Statistics*, 83, 218-231.

Layton, A. P., (1996), "Dating and Predicting Phase Changes in the U.S. Business Cycle", *International Journal of Forecasting* 12, 417-428.

McConnell, Margaret M., and Gabriel Perez-Quiros, (2000), "Output Fluctuations in the United States: What Has Changed Since the Early 1980s?" *American EconomicReview*, 90, 1464-1476.

Nalewaik, J. J., (2007), "Estimating Probabilities of Recession in Real Time Using GDP and GDI", *Finance and Economics Discussion Series 2007-07*, Board of Governors of the Federal Reserve System.

Orphanides, Athanasios, (2001), “Monetary Policy Rules Based on Real-Time Data.” *American Economic Review*, 91, 964–985.

Orphanides, Athanasios, and Simon van Norden, (2002), “The Unreliability of Output Gap Estimates in Real Time”, *Review of Economics and Statistics* 84, 569-583.

Silvapulle, P., Moosa, Imad A. and M. J. Silvapulle, (2004), “Asymmetry in Okun’s Law”, *Canadian Journal of Economics*, 37 (2), 353-74.

Stock, J. H. and M. W. Watson, (1989), “New Indexes of Coincident and Leading Economic Indicators”, *NBER Macroeconomics Annual*, 4, 351-393.

Stock, J. H. and M. W. Watson, (1991), “A Probability Model of the Coincident Economic Indicators”, in *Leading Economic Indicators: New Approaches and Forecasting Records*, ed. K. Lahiri and G. H. Moore, Cambridge: Cambridge University Press, 63-89.

Stock, J. H. and M. W. Watson, (2005), “Implications of Dynamic Factor Models for VAR Analysis”, *NBER Working Paper No. 11467*.

Table 1: Comparison of Nowcasting Results Using GDP and Industrial Production

Panel A: Univariate real-time data results based on real GDP

σ_1	μ_0	μ_1	P_U
0.740	1.001	-0.199	0.830

Panel B: Univariate revised data results based on real GDP

σ_1	μ_0	μ_1	P_U
0.732	1.066	-0.127	0.818

Mean absolute deviation between probabilities of recession from real-time data and revised data in the univariate model: 0.095

Panel C: Bivariate real-time data results based on real GDP and industrial production

σ_1	σ_2	ρ_{12}	μ_0	μ_1	γ_0	γ_1	P_B
0.748	1.257	0.656	0.916	-0.468	1.130	-1.187	0.912

Panel D: Bivariate revised data results based on real GDP and industrial production

σ_1	σ_2	ρ_{12}	μ_0	μ_1	γ_0	γ_1	P_B
0.758	1.169	0.654	0.950	-0.410	1.099	-2.001	0.939

Mean absolute deviation between probabilities of recession from real-time data and revised data in the bivariate model: 0.036

Note: The numbers reported are average parameter estimates of samples from 1969:4 – 1989:4 to 1969:4 – 2008:1. The univariate results are for real GDP growth model. The bivariate models include real GDP growth and industrial production growth.

Table 2: Comparison of Nowcasting Results Using GDP and Payroll Employment

Panel A: Univariate real-time data results based on real GDP

σ_1	μ_0	μ_1	P_U
0.745	1.072	-0.242	0.858

Panel B: Univariate revised data results based on real GDP

σ_1	μ_0	μ_1	P_U
0.744	1.158	-0.158	0.852

Mean absolute deviation between probabilities of recession from real-time data and revised data in the univariate model: 0.083

Panel C: Bivariate real-time data results based on real GDP and payroll employment

σ_1	σ_2	ρ_{12}	μ_0	μ_1	γ_0	γ_1	P_B
0.747	0.253	0.607	1.042	-0.268	0.794	-0.501	0.839

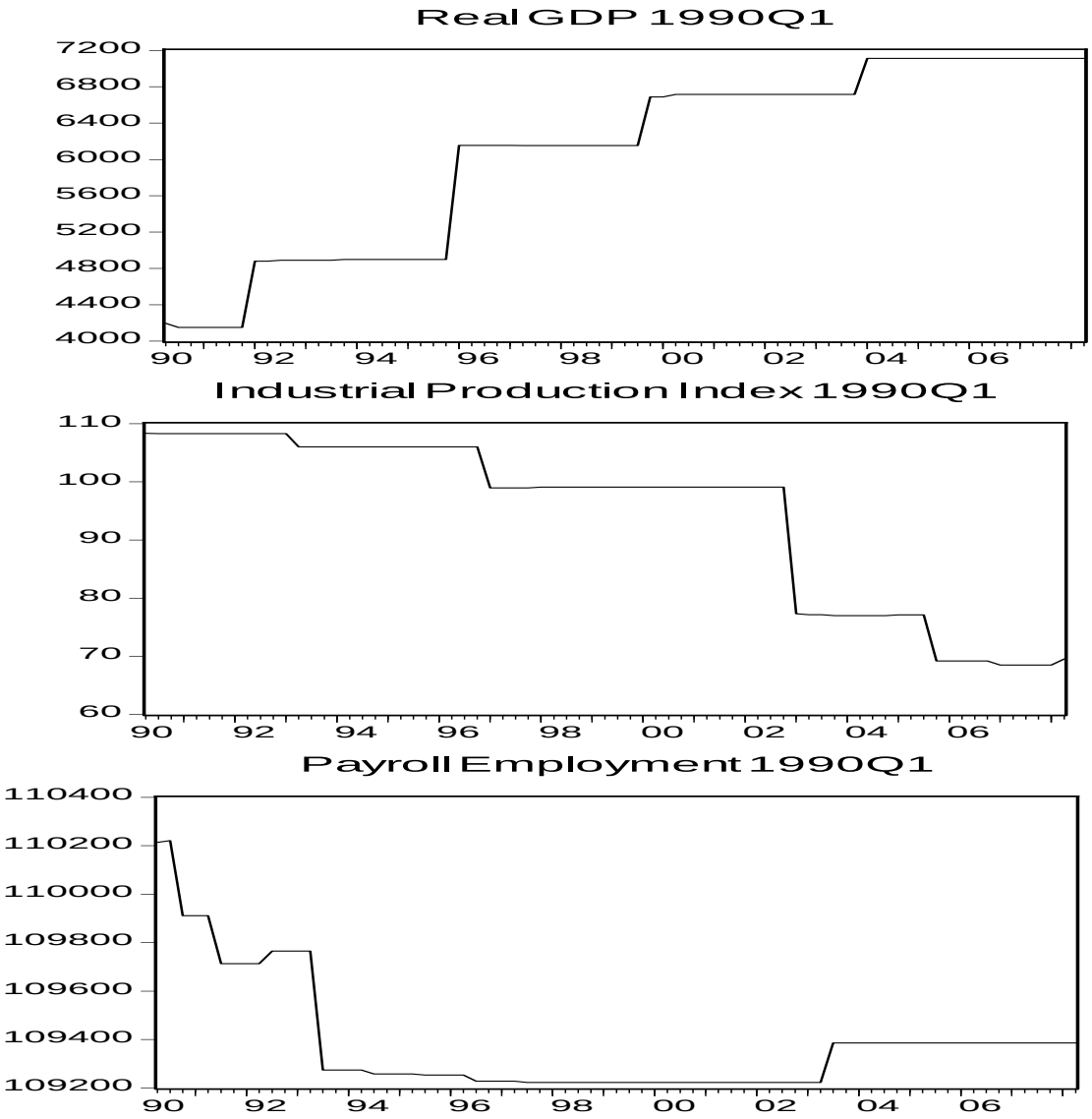
Panel D: Bivariate revised data results based on real GDP and payroll employment

σ_1	σ_2	ρ_{12}	μ_0	μ_1	γ_0	γ_1	P_B
0.755	0.245	0.612	1.111	-0.179	0.794	-0.433	0.857

Mean absolute deviation between probabilities of recession from real-time data and revised data in the bivariate model: 0.060

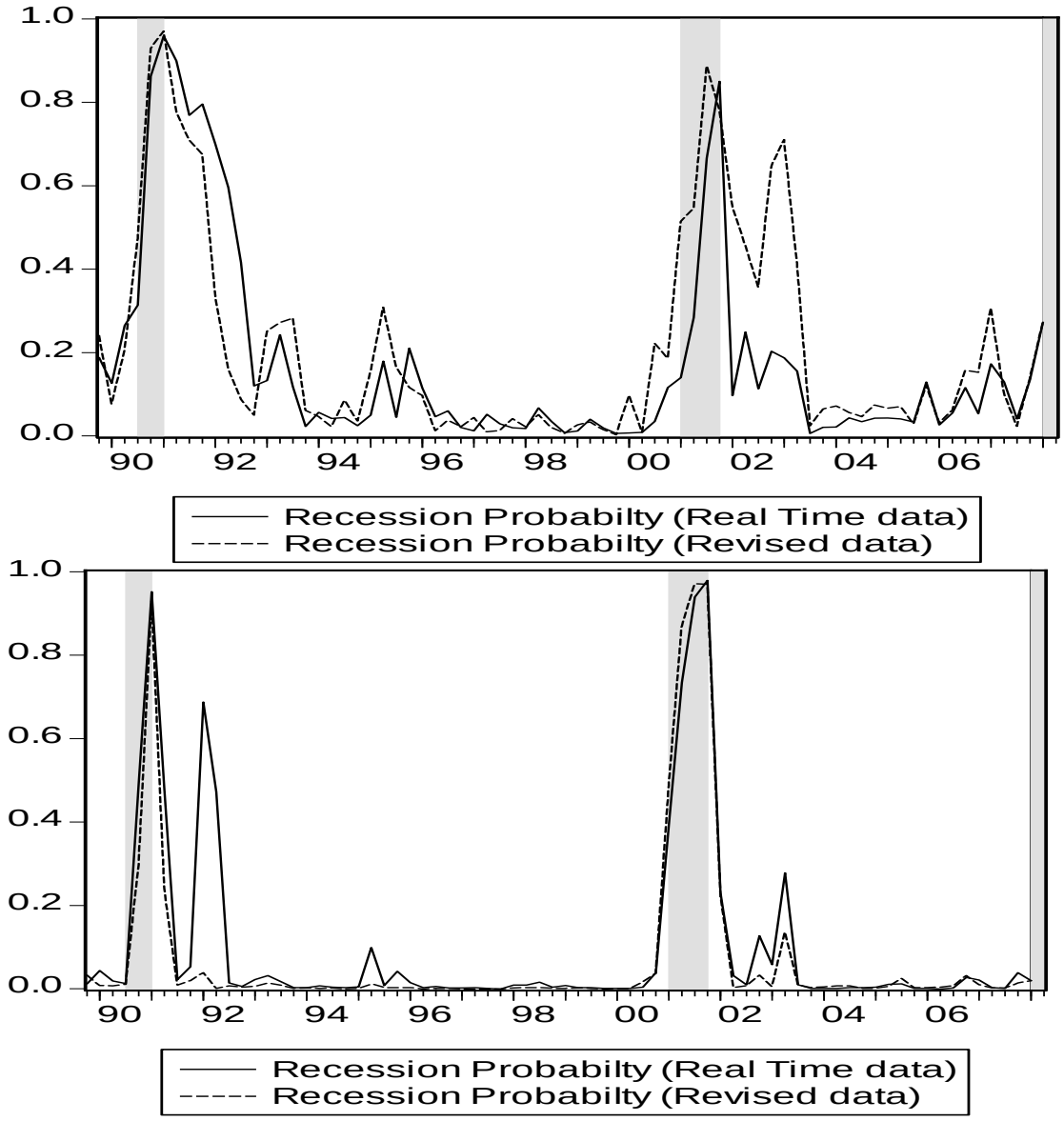
Note: The numbers reported are average parameter estimates of samples from 1959:4 – 1984:4 to 1959:4 – 2008:1. The univariate results are for real GDP growth model. The bivariate models include real GDP growth and payroll employment growth.

Figure 1: Revisions of the 1990 Quarter 1 Data



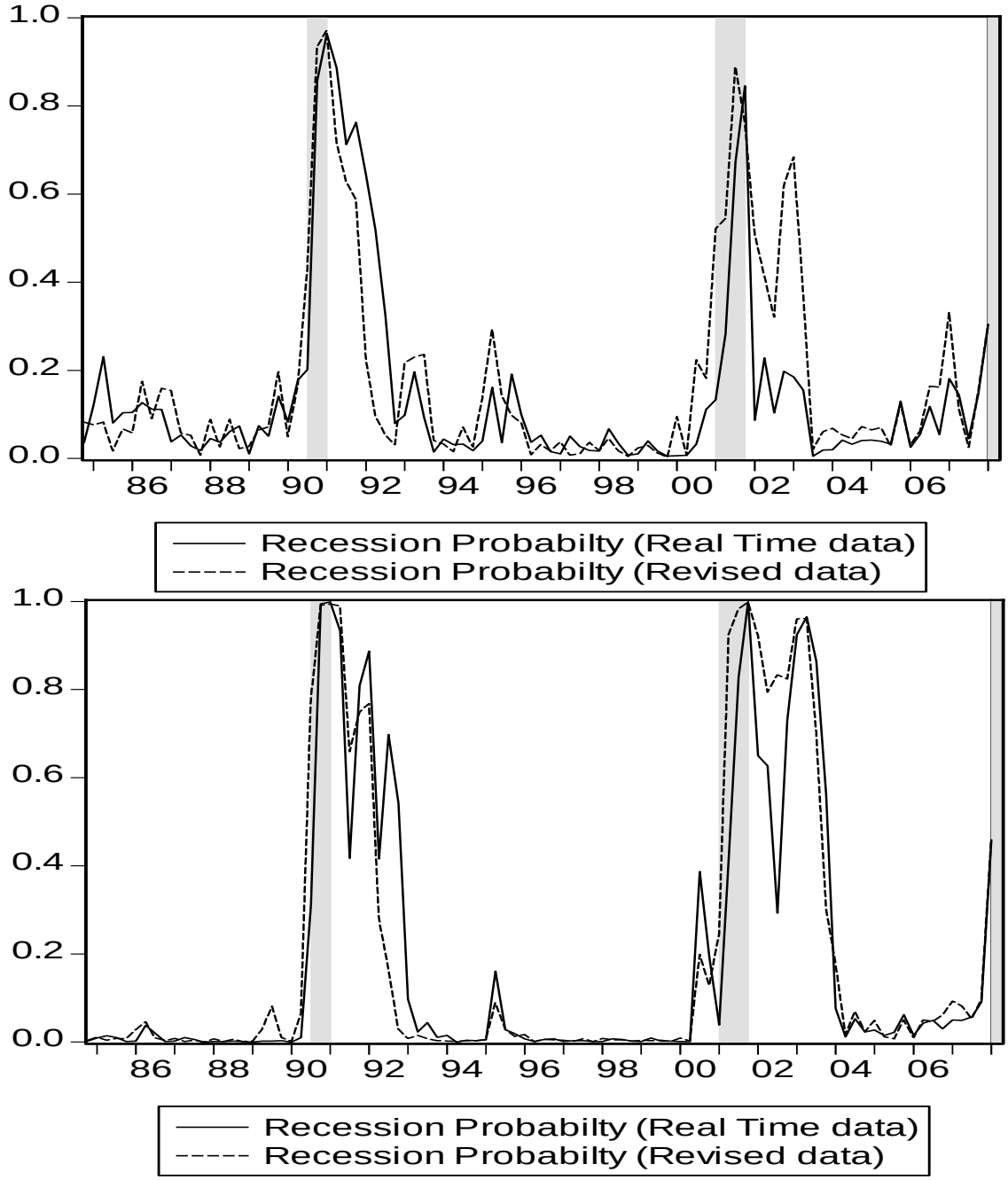
Note: The top panel shows the revisions of the real GDP data for the first quarter of 1990. The middle panel shows the revisions of the industrial production index for the first quarter of 1990. The bottom panel shows the revisions of the non-farm payroll employment data for the first quarter of 1990.

Figure 2: Nowcasted Probabilities of Recession based on GDP and Industrial Production



Note: All the above figures are nowcasted probability estimates of recession based on samples from 1969:2 – 1989:4 to 1969:2 – 2008:1. The top panel is from the univariate real GDP growth model. The bottom panel is from the bivariate model of real GDP growth and indiustrial production growth. In each panel the solid line shows the probability of recession based on real time data and the dashed line is the probability of recession based on revised data (vintage second quarter of 2008). The shaded areas are the NBER reported recession quarters.

Figure 3: Nowcasted Probabilities of Recession based on GDP and Payroll Employment



Note: All the above figures are nowcasted probability estimates of recession based on samples from 1959:4 – 1984:4 to 1959:4 – 2008:1. The top panel is from the univariate real GDP growth model. The bottom panel is from the bivariate model of real GDP growth and payroll employment growth. In each panel the solid line shows the probability of recession based on real time data and the dashed line is the probability of recession based on revised data (vintage second quarter of 2008). The shaded areas are the NBER reported recession quarters.