Real-Time Macroeconomic Monitoring: Real Activity, Inflation, and Interactions

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Abstract

We sketch a framework for monitoring macroeconomic activity in real-time and push it in new directions. In particular, we focus not only on real activity, which has received most attention to date, but also on inflation and its interaction with real activity. As for the recent recession, we find that (1) it likely ended around July 2009; (2) its most extreme aspects concern a real activity decline that was unusually long but less unusually deep, and an inflation decline that was unusually deep but brief; and (3) its real activity and inflation interactions were strongly positive, consistent with an adverse demand shock.

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1 Introduction

Real economic agents, making real decisions in real time, need accurate and timely estimates of the state of macroeconomic activity. Every day, literally millions of economic agents (business people, retail and institutional investors, financial institutions, economists, households, ...) explicitly or implicitly attempt to form and update views on macroeconomic activity as new information arrives. Significant parts, for example, of the first few pages of any day's *Wall Street Journal* or *Financial Times* are typically devoted to recently-released or soon-to-be-released data and its likely implications for business conditions.

To help meet this demand, we have earlier supplied and illustrated a framework for high-frequency measurement of macroeconomic activity in a systematic, replicable, and statistically optimal manner (Aruoba et al. (2009)).[1] We are hardly alone in appreciating the desirability and benefits of high-frequency measurement, however, as interest in the area has escalated rapidly. Academic research on high-frequency (indeed real-time) macroeconomic measurement is now voluminous, with leading reference works featuring it prominently (e.g., Croushore (2006)), and recently-established annual conferences chronicling and promoting new developments.[2] Even Google is now in the game, as industry and academics work together to expand the frontier; see Choi and Varian (2009).

Improved real-time macroeconomic measurement is of interest not only to private agents, but also to policy makers. Both groups seek to use better information to make better decisions. Hence central banks and NGOs worldwide have recently devoted significant resources to real-time macroeconomic monitoring, as for example with the Federal Reserve Bank of Philadelphia's Real-Time Data Research Center[3], the Bank of Italy and CEPR's EuroCOIN project[4], and the Bank of Spain's Euro-STING project.[5]

Similarly, leading policy-oriented academic macroeconomists are focusing squarely on real-time challenges, grappling with policy formulation and evaluation in the face of evolving current information, as for example in John Taylor's inaugural Feldstein address to the NBER (Taylor (2009)).

[1]See also our more refined real-time implementation and additional materials maintained by the Federal Reserve Bank of Philadelphia at http://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index.

[2]See for example the ongoing series of "Real-Time Data Conferences" sponsored by CIRANO (Montreal), the most recent of which is the October 2009 Fifth Annual Workshop on Data Revision in Macroeconomic Forecasting and Policy.

[3]See http://www.philadelphiafed.org/research-and-data/real-time-center.

[4]See Altissimo et al. (2007), and for recent details see http://eurocoin.cepr.org.

[5]See Camacho and Perez-Quiros (2009).

Against this background, in this paper we provide both retrospective and prospective assessment of progress in real-time macroeconomic monitoring. We focus not only on real macroeconomic activity, which has received most attention to date, but also on inflation and its interaction with real activity. In section 2 we present our basic dynamic factor framework, which we use throughout. In section 3 we use the framework to assess real activity (section 3.1), inflation (section 3.2), and their interaction (section 3.3). We conclude in section 4.

2 A Dynamic Factor Model for Economic Indicators

Our concern is with accurate real-time assessment of current macroeconomic activity; that is, our concern is with "nowcasting," not forecasting. Accurate nowcasting promotes good decision making, and although far from simple, nowcasting can likely be done with greater success than longer-horizon forecasting.[6] We work in a "small data" environment in the sense of Diebold (2003), with roughly a half-dozen indicators of economic activity.[7] We prefer small data because it lets us devote the necessary care and attention to the selection and monitoring of indicators. In addition, recent work reveals that maximum-likelihood estimation in small-data frameworks has surprisingly good properties, even when the true data-generating process is "big-data".[8]

We observe a variety of indicators, all of which contain information about the latent state of economic activity. Hence we work in a state space framework with multiple indicators and a single latent activity factor, which we extract optimally using the Kalman filter. We use mixed-frequency data, specifying the model at high frequency and allowing for a large amount of missing data (for the less-frequently observed variables).

Building directly on important earlier work of Stock and Watson (1989) and Mariano and Murasawa (2003), we postulate dynamic factor structure at high frequency. (With no loss of generality, call the highest frequency "daily".) The latent macroeconomic activity factor x_t evolves daily with covariance-stationary autoregressive dynamics,

$$x_t = \rho_1 x_{t-1} + ... + \rho_p x_{t-p} + \eta_t, \tag{1}$$

where η_t is a white noise innovation with unit variance. The i-th covariance-stationary daily

[6] In the jargon of business conditions indexes, we seek to produce coincident, not leading, indexes of economic activity. Coincident indexes are more fundamental, as a leading index is simply a forecast of a coincident index.

[7] The exact number of indicators depends on the application, as we describe subsequently.

[8] See Doz et al. (2006), Jungbacker and Koopman (2008), and Bai and Ng (2008).

indicator $\hat{y}_t^i$ may depend linearly on x_t and q^i own-lags:

$$\hat{y}_t^i = c^i + \beta^i x_t + \gamma_1^i \hat{y}_{t-D^i}^i + \gamma_2^i \hat{y}_{t-(2D^i)}^i + ... + \gamma_{q^i}^i \hat{y}_{t-(q^i D^i)}^i + \varepsilon_t^i, \tag{2}$$

where D^i is the number of days in the observational frequency of indicator i (e.g., D^i=7 if $\hat{y}_t^i$ is observed weekly), and where the ε_t^i are white noise shocks, uncorrelated with each other and with η_t.

Note that most indicators, although evolving daily, are not *observed* daily. If y_t^i denotes $\hat{y}_t^i$ observed at a lower frequency, then the relationship between y_t^i and $\hat{y}_t^i$ depends on whether $\hat{y}_t^i$ is a stock or flow variable. If $\hat{y}_t^i$ is a stock, then $y_t^i = \hat{y}_t^i$ when y_t^i is observed, and y_t^i is "missing" otherwise. Alternatively, if $\hat{y}_t^i$ is a flow, then $y_t^i = \sum_{j=0}^{D^i-1} \hat{y}_{t-j}^i$ when y_{t-j}^i is observed, and y_t^i is missing otherwise.

Our framework corresponds to a state space system: $y_t = Z\alpha_t + \Gamma w_t + \varepsilon_t$, $\alpha_{t+1} = T\alpha_t + R\eta_t$, $\varepsilon_t \sim (0, H)$, $\eta_t \sim (0, Q)$, $t = 1, ..., \mathcal{T}$, where y_t is a vector of observed variables, α_t is a vector of state variables, w_t is a vector containing ones and lagged dependent variables, and $\mathcal{T}$ denotes sample size. In general, y_t will contain many missing observations, reflecting not only missing daily data due to holidays, but also, and more importantly, the fact that most variables are observed less often than daily. In addition, several of the system parameter matrices may be time-varying, because of variation in D^i across t (e.g., different months contain different numbers of days). Note also that flow variables generally produce very high-dimensional state vectors, because observed flow variables depend on x_t and $max_i\{D^i\} - 1$ lags of x_t, which produces a state vector of dimension $max\{max_i\{D^i\}, p\}$, in contrast to the p-dimensional state associated with a system involving only stock variables.

Importantly for us, and despite the missing data and potentially time-varying system matrices, the standard Kalman filter and associated likelihood evaluation via prediction-error decomposition remain valid in our environment, subject to some simple modifications. This is well-known, as discussed for example in Durbin and Koopman (2001) and exploited in Aruoba et al. (2009) and Aruoba and Diebold (2009). In addition, the "Harvey cumulator" (Harvey, 1989, pp. 313-318) eliminates the dimensionality problem by recognizing that the state space measurement equation requires only the sums of current and $D^i - 1$ lags of x_t, not each of the summands separately. The upshot: We can use simple modifications of the standard Kalman filter and smoother to produce exact maximum-likelihood estimates of our model, and to produce optimal estimates of its latent macroeconomic activity factor, x_t. We now proceed to do so.

3 Monitoring Macroeconomic Activity

We have described real activity monitoring in Aruoba et al. (2009), and we have provided enhancements in Aruoba and Diebold (2009). Indeed the so-called ADS Index is now maintained by the Federal Reserve Bank of Philadelphia, updated in real time and written to the web whenever new data, or revisions of existing data, are released.[9] Here we push the ADS framework in new directions, focusing not only on real activity, but also on inflation and its interaction with real activity.

To maximize transparency, in this paper we use a *monthly* base frequency for both real activity and inflation analysis, eliminating many of the complications mentioned earlier (time-varying system matrices, high-dimensional state vectors, etc.) We use indicators seasonally adjusted by the relevant reporting agency. We transform all indicators to logarithmic changes; hence all are flows. We allow for $p = 3$ autoregressive lags in the transition equation (1). We allow for $q^i = 3/D^i$ own autoregressive lags in the measurement equation (2); that is, we allow for one (quarterly) lag of quarterly variables, and we allow for three (monthly) lags of monthly variables.

3.1 Real Activity

We use five indicators, from the 11/23/2009 data vintage: payroll employment (monthly, from the Bureau of Labor Statistics (BLS), 1960.02-2009.10), industrial production (monthly, from the Federal Reserve Board (FRB), 1960.02-2009.10), real personal income less transfers (monthly, from the Bureau of Economic Analysis (BEA), 1960.02-2009.09), real manufacturing and trade sales (monthly, from Census, 1967.02-2009.08), and real GDP (quarterly, from BEA, 1960.II-2009.III). Note in particular the different ending dates of the indicators in the 11/23/2009 vintage, as is typical, due to differing release timeliness.

We plot the five indicators, together with NBER "recession bars", in the top panel of Figure 1, where it is apparent that idiosyncratic noise in the individual indicators masks much of the real activity information contained in them.[10] Hence any single indicator is of severely limited value for tracking the business cycle.

The extracted real activity factor, in contrast, is much less noisy, as seen in the middle panel of Figure 1. The estimation results (not shown to save space) reveal that all indicators load positively and significantly on the real activity factor in our estimated equation (2).

[9] See http://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index.

[10] We end the last recession bar in July 2009, which is when our real activity factor returns to zero.

Conversely, the extracted factor is driven by all of the underlying indicators. In optimally extracting the state of real activity, however, the Kalman filter effectively eliminates much of the idiosyncratic noise by averaging both over the cross section and over time.

Several features of the middle panel of Figure 1 are noteworthy (as highlighted in Figure 2, which contains real activity plots during 36-month windows containing the six most recent recessions). First the "Great Moderation" in the volatility of real activity, roughly 1985-2007, is clear, even if now relegated to the dustbin of history. Second, movements in our real activity factor clearly cohere with the NBER chronology. And finally, the recent recession is revealed to be quite deep, and most notably very long, relative to its post-1960 competitors.[11] This extreme "duration severity" interacts with the moderately extreme "depth severity" to produce *very* extreme overall severity.

Let us expand briefly on the recent recession, which is of special interest. In the bottom panel of Figure 1 we show the most recent two years of the real activity index, which begins its plunge in very late 2007, in accord with the NBER's dating. Moreover, the index shows a clear trough in January 2009, after which it recovers steadily, with the recession ending (in our assessment) in July 2009.[12] Hence the recent recession is extremely long by post-1960 – indeed even postwar – standards.[13]

3.2 Inflation

Our approach to measuring inflation parallels precisely our approach to measuring real activity.[14] As with real activity indicators, we see many inflation indicators, each of which contains potentially valuable, but incomplete and noisy, information about the underlying common component. We include wages among our indicators because they are a crucially important price, and one not not explicitly contained in standard price indexes.

Our inclusion of wages has both theoretical and empirical nuances. On the theoretical side, inclusion of wages is motivated by modern dynamic stochastic general equilibrium

[11] As of the date of writing (January 2010), its NBER ending date remains undeclared. As mentioned earlier, however, our results indicate an ending date of approximately July 2009.

[12] The trough in September 2008 was caused by a set of exogenous events and should be discounted entirely. In particular, September industrial production was severely affected by a largely exogenous "triple shock" (Hurricanes Gustav and Ike, and a strike at a major aircraft manufacturer), which caused an annualized September 2008 drop of nearly fifty percent and a correspondingly huge October rebound. September/October manufacturing and trade sales behaved similarly.

[13] See Diebold and Rudebusch (1992) for discussion and analysis of recession durations.

[14] Hence, for example, our focus is very different from the recent work of Reis and Watson (2009), who use only prices of consumption goods and use a dynamic factor model to decompose them in a way that helps make contact with modern theories of inflation dynamics.

models, which suggest that optimal monetary policy rules may be approximated by Taylor-type rules that respond to price inflation *and* wage inflation (e.g., Schmitt-Grohe and Uribe (2007)) or even wage inflation exclusively (e.g., Levin et al. (2006)).

On the empirical side, inclusion of wages raises the issue of what wage indicator(s) to use. Wage indicators effectively fall into one of two camps, "hourly compensation" or "unit labor cost". We focus on hourly compensation, as unit labor costs confound wage-rate movements with productivity movements.

We use six inflation indicators from the 11/23/2009 data vintage: the all-items CPI (monthly, from BLS, 1960.01-2009.10), the finished-goods PPI (monthly, from BLS, 1960.01-2009.10), a non-energy commodity price index (monthly, Standard and Poor's GSCI Non-Energy Commodities Index, 1970.01-2009.10), a spot oil price (monthly, West Texas Intermediate, from FRB St. Louis FRED database, 1960.01-2009.10), the GDP deflator (quarterly, from BEA, 1960.I-2009.III), and hourly compensation in the non-farm business sector (quarterly, from BLS, 1960.I-2009.III).

We plot the six inflation indicators, together with NBER recession bars, in the top panel of Figure 3. The wide scaling is due to the oil price, which swings widely beginning in the mid-1970s. As with real activity indicators, idiosyncratic noise in the inflation indicators masks much of their information, rendering the individual indicators of limited value for tracking inflation.

We again use the Kalman filter to estimate a simple dynamic factor model and extract the latent state, resulting in an inflation index. The extracted inflation factor, although still somewhat noisy, is nevertheless less noisy than the component indicators, as seen in the middle and rightbottom panels of Figure 3. The estimation results (not shown to save space) reveal that all indicators load significantly on the factor in our estimated equation (2).

Several features of the middle panel of Figure 3 deserve mention. First, the inflation of the 1970s is apparent, as is its retreat, which began with Paul Volcker's appointment as Chairman of the Federal Reserve Board in August 1979, and which ended by 1983 or so. Second, not only inflation's level, but also its *volatility*, was low from then until the late 1990s. In contrast, inflation volatility shows a marked increase from the late 1990s onward, a phenomenon potentially linked to inflation's recent decreased forecastability, as documented by Stock and Watson (2007).

Finally, the recent period 2007-2009 is especially important, so we zoom in on it in the bottom panel of Figure 3. The historically-unprecedented (at least since 1960) 2008 inflation drop was extremely sharp but also extremely brief. The entire episode ultimately lasted just six months.

3.3 Interactions

Prices and quantities should be related over the business cycle, and the nature of the relationship should convey information about the sources of shocks. (Demand shocks produce positive price-quantity correlation and supply shocks produce negative price-quantity correlation.) Hence we now proceed to examine real activity and inflation *together* over the cycle.

We plot our real activity and inflation indexes in the top panel of Figure 4, together with NBER recession bars. We plot real activity on the left scale (wide font) and inflation on the right (thin font), so that movements in the two series do not obscure each other. Movements in real activity and inflation do indeed cohere over the business cycle. Moreover, and crucially, the nature of the coherence depends on whether recessions are demand- or supply-driven. The inflation index tends to drop in most recessions, consistent with adverse demand shocks, as for example in the "Volcker recession" of the early 1980s, which most analysts believe was demand-driven. In contrast, the mid-1970s and 1980 oil shock recessions show decreased real activity and *increased* inflation, consistent with adverse supply shocks.

In the bottom panel of Figure 4 we zoom in on the recent recession. Inflation falls both more sharply and later than real activity, plunging only in summer 2008, whereas real activity begins its descent in 2007. Inflation also *recovers* both more sharply and *sooner* than real activity, returning to baseline within approximately six months.

If differing descent and rebound patterns in real activity and inflation during the recent recession are interesting, the similarities are also striking and ultimately more important. The bottom panel of Figure 4 clearly shows strong positive co-movement of real activity and inflation during the recent recession, consistent with an adverse demand shock.

4 Summary and Concluding Remarks

We have used a dynamic-factor approach to extract indexes of U.S. real activity and inflation. Key aspects of our approach are its use of high-frequency data, its natural implementation in a state-space environment via Kalman filtering, and its related natural facilitating of real-time updating as data are released.

Historically, our real activity index closely matches the NBER chronology and captures widely-discussed phenomena such as the "Great Moderation". Our inflation index also follows the cycle, with the sign of the correlation varying, depending on whether various recessions are supply- or demand-driven.

The recent recession is of central interest, not least because of its severity. In terms of real activity, our results indicate that it was among the most severe since 1960. Interestingly, however, the *depth* of its real activity decline does not appear to be the largest since 1960, as the the mid-1970s and 1980 recessions were a bit deeper. Instead, the most unusual aspect of the recent recession's real activity movement is its *duration*. This extreme "duration severity" interacts with the moderately extreme "depth severity" to produce *very* extreme overall severity. A second extreme movement during the recent recession concerns inflation as opposed to real activity – the 2008 drop is by far the most pronounced on record since 1960. Finally, real activity and inflation appear strongly positively correlated during the recent recession, consistent with an adverse demand shock.

The work begun here can be extended in several potentially fruitful directions. In work in progress, for example, we assess the possible presence of regime-switching in extracted factors, as in Diebold and Rudebusch (1996), both from the highbrow perspective of incorporating nonlinear aspects of the cycle, and from the pragmatic perspective of transforming our indexes in ways that may enhance their interpretability. In addition we are extending our framework to the global environment, estimating a hierarchical global dynamic factor model in the tradition of Kose et al. (2003), with country indicators depending on country factors, country factors potentially depending on regional factors, and regional factors potentially depending on global factors.

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Figure 1: Real Activity Indicators and Extracted Real Activity Index

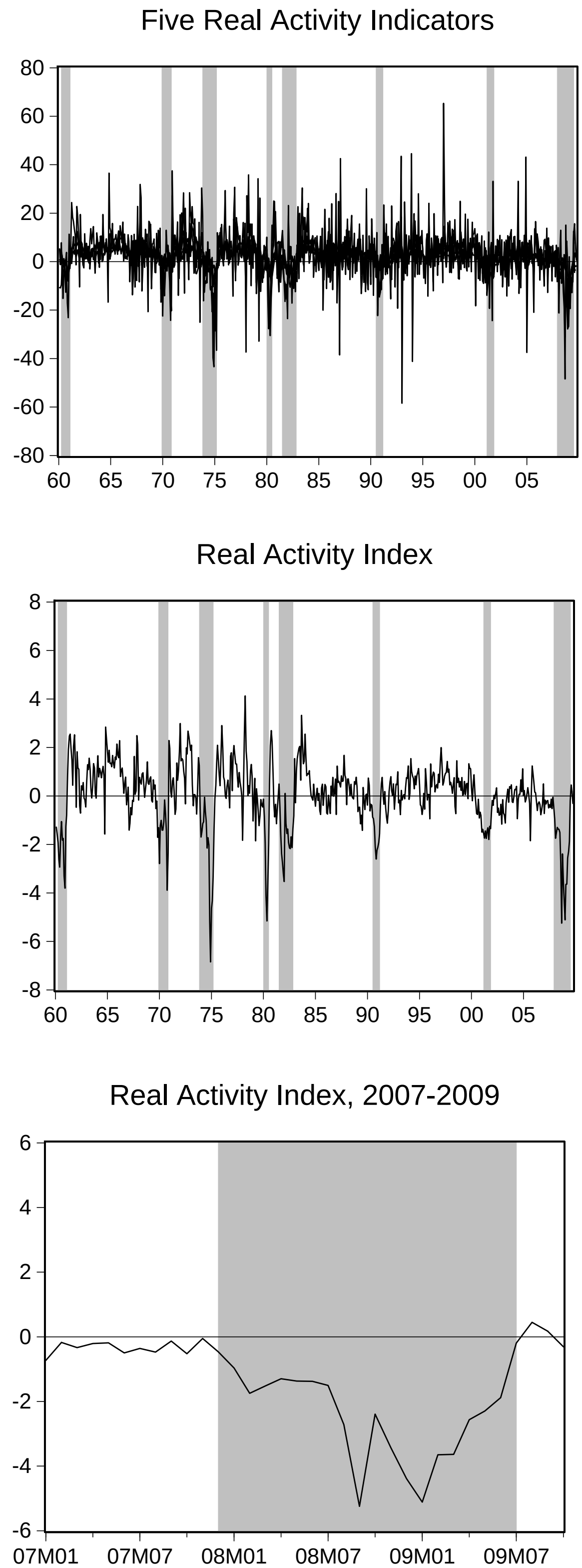

Figure 2: Real Activity Index During Recessions

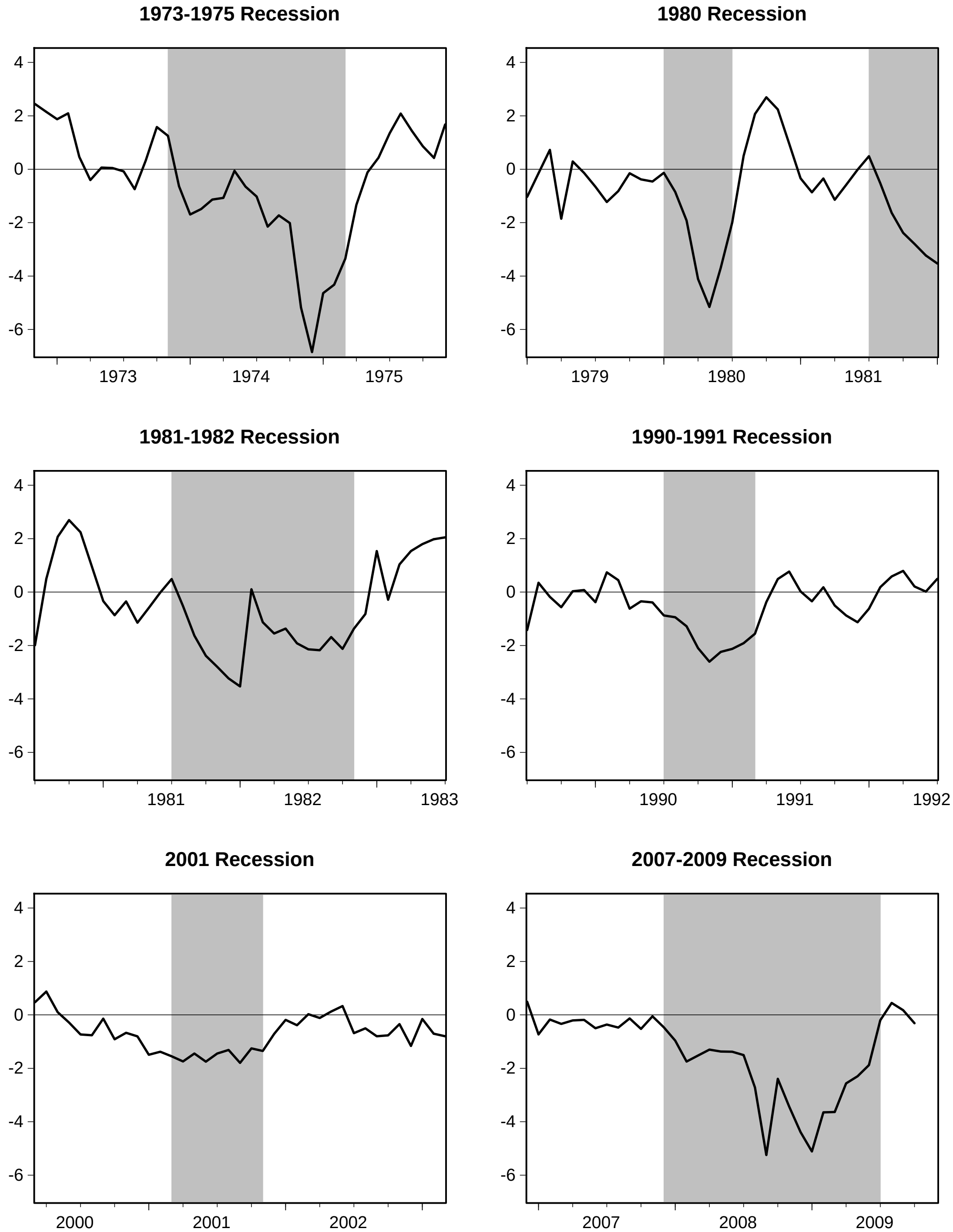

Figure 3: Inflation Activity Indicators and Extracted Inflation Index

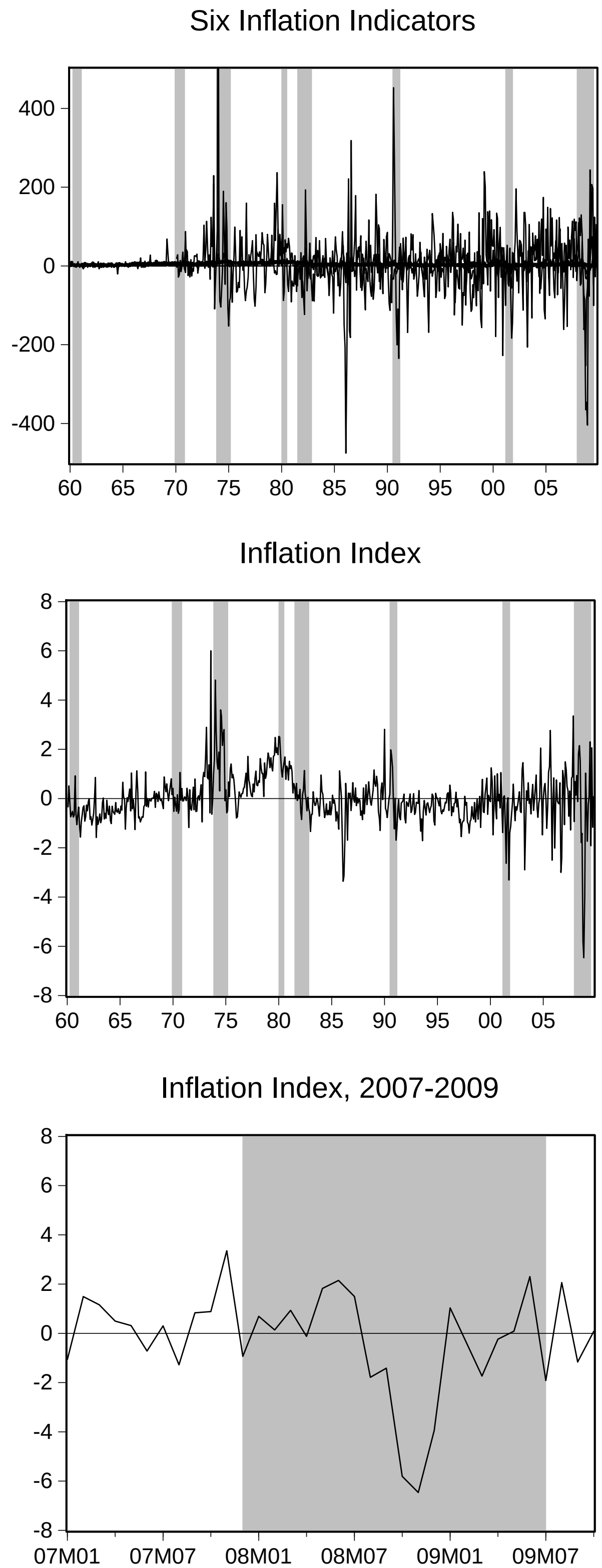

Figure 4: Real Activity and Inflation Over the Cycle