FORECASTING IN DYNAMIC FACTOR MODELS SUBJECT TO STRUCTURAL INSTABILITY

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1. Introduction

An ongoing theme in David Hendry's work has been concern about detecting and avoiding forecast breakdowns that arise because of structural instability. Parameter instability can arise for various reasons, including structural breaks in the economy (for example, changes in technology), policy regime shifts, or changes in the survey instruments from which the time series are constructed. Hendry and coauthors have argued that such instability, whatever its source, often manifests itself as breaks in time series forecasting relations, and moreover that such breaks constitute one of the primary reasons for forecast failures in practice (see for example Clements and Hendry [1999, 2002], Hendry and Clements [2002], Hendry [2005], and Hendry and Mizon [2005]). One line of Hendry's research has been to develop and to analyze non-structural forecasting methods for their potential to be robust against parameter instability, including error correction models, overdifferencing, intercept shift methods, and – closest to the focus of this paper – forecast pooling (Hendry and Clements [2002]).

This paper continues this line of inquiry, in which forecasting methods are examined for their reliability in the face of structural breaks, focusing specifically on forecasts constructed using dynamic factor models (DFMs; Geweke [1977], Sargent and Sims [1977]). In DFMS, the comovements of the observable time series are characterized by latent dynamic factors. Over the past decade, work on DFMs has focused on high-dimensional systems in which very many series depend on a handful of factors (Forni, Lippi, Hallin, and Reichlin [2000], Stock and Watson [2002a, 2002b], and many others; for a survey, see Stock and Watson [2005]). These factor-based forecasts have had notable empirical forecasting successes. Yet, there has been little published theoretical or empirical work to date on the performance of factor-based macroeconomic forecasts under structural instability.

Despite this dearth of research on factor models and structural instability, at a conceptual level there are reasons to think that factor models might be robust to certain types of structural instability, for reasons akin to those discussed in Hendry and Clements (2002) in the context of forecast pooling. Hendry and Clements (2002) consider forecast breakdowns arising from intercept shifts, which in turn arise from shifts in the means of omitted variables. These intercept breaks doom any one forecasting regression in which they arise, but if one averages over many forecasts, and if the intercept shifts are sufficiently uncorrelated across the different forecasting regressions, then the intercept shifts average out and the pooled forecast is relatively more robust to this source of structural instability than any of the constituent forecasting regressions. In factor models, a similar logic could apply: even if factor loadings are unstable, if the instability is sufficiently independent across series then using many series to estimate the factors could play the same "averaging" role as the pooling of forecasts, and the estimated factors could be well estimated even if individual relations between the observable series and the factors are unstable. Given well-estimated factors, forecasts can be made by standard time-varying parameter or rolling regression methods.

This paper provides some initial theoretical and empirical results concerning the estimation of dynamic factors and their use for forecasting when there is structural instability in the underlying factor model. Section 2 lays out the time-varying DFM and categorizes the implications for forecasting when the model is subject to different types of structural instability (breaks in the factor loadings, in the factor dynamics, and in the idiosyncratic dynamics). In Section 3, we state a theorem that provides conditions under which the principal components estimator of the factors still spans the space of the true factors despite time variation in the factor loadings.

We then turn to an empirical examination of instability in DFMs using a data set (described in Section 4) consisting of 145 quarterly macroeconomic time series for the United States, spanning 1959 – 2006. Motivated by the literature on the Great Moderation, we consider split-sample instability with a single break in 1984. The results are summarized in Section 5. We find considerable instability in the factor loadings around the 1984 break date, but – despite this instability – principal components provides stable estimates of the factors. In consequence, factor-based forecasts of individual variables can use full-sample estimates of the factors but should use subsample (or time-varying) estimates of the regression coefficients.

2. The Time-Varying Dynamic Factor Model and Implications for Factor-Based Forecasts

This section sets out the time-varying dynamic factor model and examines the separate implications for forecasting of structural breaks in the factor loadings, in the factor dynamics, and in the idiosyncratic dynamics.

2.1 The Time-Varying Factor Model

We work with the static representation of the dynamic factor model,

$$X_t = \Lambda_t F_t + e_t, \tag{1}$$

where $X_t = (X_{1t},..., X_{nt})'$, $e_t = (e_{1t},..., e_{nt})'$, and F_t is r-vector of static factors, and $E(\nu_{it}|F_{t-1}, F_{t-2},\ldots, X_{it-1}, X_{it-2},\ldots) = 0$. The difference between (1) and standard formulations is that we consider the possibility that the factor loadings, Λ_t, can change over time.

Although a parametric specification of the factor dynamics and the factor loadings is not needed to estimate the factors, such parametric specifications are useful when discussing forecasts using the factors. We therefore suppose finite-order autoregressive dynamics for the factors and idiosyncratic term:

$$F_t = \Phi_t F_{t-1} + \eta_{it} \tag{2}$$

$$e_{it} = a_{it}(\mathrm{L})e_{it\text{-}1} + \varepsilon_{it},\ i = 1,\ldots, n, \tag{3}$$

The static factor model (1) - (3) can be derived from dynamic factor model assuming finite lag lengths and VAR factor dynamics in the dynamic factor model, in which case F_t contain lags of the dynamic factors and Φ is a companion matrix so that the static factor dynamics are first order.

The model (1) - (3) can be thought of as the reduced form of a structural model. To be concrete, it is useful to think of Boivin and Giannoni's (2006) setup (which extends

Sargent [1989] to many observable variables), in which the factor dynamics (2) are the reduced form representation of a dynamic stochastic general equilibrium (DSGE) model. The unobserved state variables – the factors – are each measured by multiple direct sensor variables; for example the DSGE concept of output is measured by multiple actual output series, where each measure of output has its own idiosyncratic component, due in part to measurement error and in part to differences between the measurement concept and the underlying DSGE state variable concept. In addition to these direct sensor variables, in which zeros in the factor loading matrix are imposed, there are additional informational or expectational variables for which there are no *a-priori* restrictions on the factor loadings.

Because the static factor model is a reduced-form model, low-dimensional changes in an underlying structural model can result in widespread time variation in the factor model parameters. A structural break in the DSGE parameters, such as a change in a monetary policy rule coefficient, would imply a structural break in Φ and/or a change in the variance of F_t. In addition, a shift in a DSGE parameter would in general induce a shift in the factor loadings for the Boivin-Giannoni (2006) informational variables, but not for the sensor variables.

2.2 Time-Varying Forecast Functions with Split-Sample Time Variation

The implications for (population) forecasting regressions depend on the source of the time variation in the DFM. For the discussion in this subsection, suppose that $E(\varepsilon_{is}| F_t, F_{t-1},\ldots, X_{it}, X_{it-1},\ldots) = E(\eta_{is}| F_t, F_{t-1},\ldots, X_{it}, X_{it-1},\ldots) = 0$ for $s > t$, and that the idiosyncratic errors $\{\varepsilon_{it}\}$ are uncorrelated with the factor disturbances $\{\eta_t\}$ at all leads and lags. For the i^{th} variable, substitution of (2) and (3) into (1) yields the one-step ahead prediction equation,

$$X_{it} = \Lambda_{it}\Phi F_{t-1} + a_{it}(\mathrm{L})e_{it-1} + \Lambda_{it}\eta_{it} + \varepsilon_{it}. \tag{4}$$

The h-step conditional expectation of X_{it} is,

$$X_{it+h|t} = E(X_{it+h}|F_t, F_{t-1},\ldots, X_{it}, X_{it-1},\ldots) = \beta_{it}^{h}{}'F_t + a_{it}^{h}(\mathrm{L})\, e_t, \tag{5}$$

where $\beta_{it}^{h}{}' = \Lambda_{it+h}\prod_{s=t+1}^{t+h}\Phi_s$ and $a_{it}^{h}(\mathrm{L})e_{it} = E[a_{it+\mathrm{h}}(\mathrm{L})e_{t+h-1}| F_t, F_{t-1},\ldots, X_{it}, X_{it-1},\ldots] =$ $E[a_{it+\mathrm{h}}(\mathrm{L})e_{it+h-1}|e_{it}, e_{it-1},\ldots]$.

Looking ahead to the empirical analysis, we consider the case of a single break at date $t = \tau$, and consider three special cases are of interest, respectively corresponding to a break in Λ, Φ, and $a_{it}(\mathrm{L})$.

Forecast function with a single break in Λ. In this case, $\Lambda_{it} = \Lambda_{i1}$, $t < \tau$, and $\Lambda_{it} = \Lambda_{i2}$, $t \geq \tau$, so (5) becomes,

$$X_{it+h} = \begin{cases} \Lambda_{i1}\Phi^h F_t + a_i(\mathrm{L})e_{it}, & t < \tau \\ \Lambda_{i2}\Phi^h F_t + a_i(\mathrm{L})e_{it}, & t \geq \tau + h \end{cases} \tag{6}$$

If the only break is in the factor loadings, then coefficients on F_t, but not those on e_{it} and its lags, change.

Forecast function when only Φ is time-varying. In this case, $\Phi_t = \Phi_1$, $t < \tau$, and $\Phi_t = \Phi_2$, $t \geq \tau$, so (5) becomes,

$$X_{it+h} = \begin{cases} \Lambda_i\Phi_1^h F_t + a_i(\mathrm{L})e_{it}, & t < \tau \\ \Lambda_i\Phi_2^h F_t + a_i(\mathrm{L})e_{it}, & t \geq \tau + h \end{cases} \tag{7}$$

If the only break is in the factor dynamics, then only the coefficients on F_t change.

Forecast function when only a_{it} is time-varying. In this case, $a_{it}(\mathrm{L}) = a_{i1}(\mathrm{L})$, $t < \tau$, and $a_{it}(\mathrm{L}) = a_{i2}(\mathrm{L})$, $t \geq \tau$, so (5) becomes,

$$X_{it+h} = \begin{cases} \Lambda_i\Phi^h F_t + a_{i1}(\mathrm{L})e_{it}, & t < \tau \\ \Lambda_i\Phi^h F_t + a_{i2}(\mathrm{L})e_{it}, & t \geq \tau + h \end{cases} \tag{8}$$

If the only break is in the idiosyncratic dynamics, then only coefficients on e_{it} and its lags change.

By working backwards, these three cases can help identify the nature of an observed structural break. Stable factor loadings in (1), combined with a break in the coefficient on F_t in (5), point to a break in the factor dynamics. Similarly, a break in the coefficients on lagged e_{it} in (5) points to a break in the idiosyncratic dynamics.

3. Estimation of Static Factors in the Presence of Time Variation

In this section, we state an unpublished result from Stock and Watson (1998) that considers estimation of the factors when there is time variation in the factor loadings. Let the factor loading matrix evolve according to,

$$\Lambda_t = \Lambda_{t-1} + h_T\zeta_t, \tag{9}$$

where h_T is sequence of $N\times N$ matrix that potentially depends on T. We consider time-varying factor loadings that satisfy the following condition:

Condition TV (time-varying factor loadings). $h_T = \text{diag}(h_{1T},\ldots, h_{NT})$, where h_{iT} is i.i.d. and independent of $\{e_t, \varepsilon_t\}$, and $T\kappa_{4T} = O(1)$, where $\kappa_{qT} = (Eh_{iT}^q)^{1/q}$.

Condition TV allows for either breaks in the factor loadings in a fraction of the series, or for moderate parameter drift in all the series. Consider the following example. Suppose a fraction π of the series are subject to a break at date τ, so that for these series $\Delta\Lambda_t = a$ if $t = \tau$ and $= 0$ otherwise. The remaining $1 - \pi$ series experience moderate parameter drift of the form $h_{iT} = b/T$ (so the full-sample parameter drift is $O(T^{-1/2})$, the same order as conventional sampling uncertainty were F_t observed; this is the Pitman drift nesting for time-varying parameters). Then $T\kappa_{qT} \to [a^qT^{q-1}\pi + b^q(1 - \pi)]^{1/q}$, so $T\kappa_{4T} = O(1)$ if $\pi = O(T^{-3})$. If $N = T^3$, this corresponds to a constant fraction of the series having a single break and the rest having moderate parameter drift.

The remaining technical conditions are similar to other conditions in the literature on factor estimation with large N. We consider approximate factor models in the sense of

Chamberlain and Rothschild (1983), so that there can be limited dependence over i and t among the idiosyncratic terms; however, that idiosyncratic dependence and the factor loadings are such that the largest r eigenvalues of $E(X'X/T)$ are $O(N)$, whereas the remaining eigenvalues are $O(1)$. For a matrix A, Let $\|A\| = (\mathrm{tr}A'A)^{1/2}$. The remaining conditions are,

Condition FL (factor loadings). $|\lambda_{i0,m}| \leq \bar{\lambda} < \infty$, $i = 1,\ldots, N$, $m = 1,\ldots, r$; $r\mathrm{mineval}(\Lambda_0'\Lambda_0/N) \geq d > 0$; $tr(\Lambda_0'\Lambda_0/N) \leq c < \infty$; and $\Lambda_0'\Lambda_0/N \to D$, where D is positive definite.

Condition M (moments and dependence). The random variables $\{e_t, \zeta_t, F_t\}$ satisfy,

(a) (*i*) $Ee_{it} = 0$, $E(e_t'e_{t+u}/N) = \gamma(u)$, and $\sum_{u=-\infty}^{\infty}|\gamma(u)| < \infty$,

(*ii*) $Ee_{it}e_{jt} = \tau_{ij}$, where $\lim_{N\to\infty} N^{-1}\sum_{i=1}^{N}\sum_{j=1}^{N}|\tau_{ij}| < \infty$,

(*iii*) $\sup_{i,t} Ee_{it}^4 < \infty$ and $\lim_{N\to\infty}\sup_{s,t} N^{-1}\sum_{i=1}^{N}\sum_{j=1}^{N}|\mathrm{cov}(e_{is}e_{it}, e_{js}e_{jt})| < \infty$.

(b) (*i*) $E\zeta_{it,m} = 0$, $E\zeta_{it}\zeta_{jt+u}' = \Gamma_{ij}(u)$, and $\sum_{u=-\infty}^{\infty}\sup_{i,j,l,m}|\Gamma_{ij,lm}(u)| < \infty$,

(*ii*) $\lim_{N\to\infty}\sup_m N^{-1}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{u=-\infty}^{\infty}|\Gamma_{ij,mm}(u)| < \infty$,

(*iii*) $\sup_{i,s.m} E\zeta_{is,m}^4 < \infty$ and

$$\lim_{N\to\infty}\sup_{l,m} N^{-1}\sum_{i=1}^{N}\sum_{j=1}^{N}\sup_{t,u_1,u_2,u_3}|\mathrm{cov}(\zeta_{it,l}\zeta_{it+u_1,m}, \zeta_{jt+u_2,l}\zeta_{jt+u_3,m})|.$$

(c) (*i*) $E\zeta_{it}e_{jt+u} = \Psi_{ij}(u)$ and $\sup_i \sum_{u=-\infty}^{\infty}\sup_m|\Psi_{ii,m}(u)| < \infty$,

(*ii*) $\sup_m N^{-1}\sum_{i=1}^{N}\sum_{j=1}^{N}\sup_{t,u,v}|\mathrm{cov}(e_{it}\zeta_{it+u,m}, e_{jt}\zeta_{jt+v,m})|$.

(d) (*i*) $\max_i\sup_t|F_{it}^0| \leq \bar{F} < \infty$.

(*ii*) $EF_t^0F_t^{0\prime} = \Sigma_{F,T}$, where $0 < d \leq \mathrm{mineval}(\Sigma_{F,T}) \leq c < \infty$.

(*iii*) $\sup_{l,m,t}\sum_{u=-\infty}^{\infty}\|\mathrm{cov}(F_{lt}^0F_{mt}^0, F_{lt+u}^0F_{mt+u}^0)\| < \infty$.

Condition *M* allows for limited dependence between the idiosyncratic term and the time variation in the factor loadings, and for ζ_t to be serially correlated.

Let $\{\hat{F}_t\}$ be estimated by principal components. We now have,

Theorem 1. Let X_t and Λ_t obey (1) and (9). Suppose that conditions TV, FL, and M, and that $T \to \infty$ and $\ln(N)/\ln(T) \to \rho > 2$. Then $\delta_{NT} \sup_t \left\| \hat{F}_t - H_{NT} F_T \right\| \to_p 0$, where $\delta_{NT} = T^b$ for any $b < \min(½\rho - 1, 1)$, and H_{NT} is not a function of (i,t).

Theorem 1 is proven in Stock and Watson (1998).

Theorem 1 says that, despite the time variation in the factor loadings, the principal components estimator of the factor asymptotically spans the space of the true factors, moreover in this theorem the principal components estimators do so uniformly. The rate condition is different than the usual condition in the literature, in which N, $T \to \infty$ without any joint restriction. Here, N increases faster than T. This plays two roles in the theorem, it is used to obtain the uniform (over t) estimation of the factors and it allows the time variation in the factors to be overcome by averaging over many series.

4. Empirical Application: the Quarterly U.S. Data Set

The empirical work employs a newly compiled data set consisting of 145 quarterly time series for the United States, spanning 1959:I – 2006:IV. The variables, sources, and transformations are listed in Appendix Table A.1. The first two quarters were used for initial values when computing first and second differences, so the data available for analysis span 1959:III – 2006:IV, for a total of $T = 190$ quarterly observations.

The full data set contains both aggregate and subaggregate series. By construction, the idiosyncratic term of aggregate series (e.g. nonresidential investment) will be correlated with the idiosyncratic term of lower-level subaggregates (e.g. nonresidential investment – structures), and the inclusion of series related by identities (an aggregate being the sum of the subaggregates) does not provide additional information useful for factor estimation. For this reason, the factor estimates were computed using the subset of 110 series that excludes higher level aggregates related by identities to the lower level subaggregates (the series used to estimate the factors are indicated in Table A.1). This represents a departure from the approach in some previous work (e.g. Stock and Watson [2002a, 2005]) in which both aggregates and subaggregates are used to estimate the factors. The data set here includes more subaggregates than the quarterly data set in Stock and Watson (2005).

The series were transformed as needed to eliminate trends by first or second differencing (in many cases after taking logarithms); see Table A.1 for specifics.

5. Empirical Results

The empirical analysis focuses on instability around a single break in 1984:I. The reason for the 1984 break date is that 1984 (more generally, the mid-1980s) has been identified as an important break date associated with the so-called Great Moderation of output (Kim and Nelson [1999], McConnell and Perez-Quiros [2000]), and there have been shifts in other properties of time series such as the inflation-output relation that can be dated to the mid- to late-80s (cf. Stock and Watson [2007]).

Our analysis of forecasting stability focuses on four-quarter ahead prediction. For real activity variables, the four-quarter object of interest, $X_{it+4}^{(4)}$, corresponds to growth over the next four quarters; for inflation measures, $X_{it+4}^{(4)}$ is average quarterly inflation over the next four quarters, minus inflation last quarter; and for variables entered in levels such as the capacity utilization rate, it is the value of that variable four quarters hence. Specifics are given in the appendix.

All forecasts are direct, specifically, forecasts of $X_{it+4}^{(4)}$ are obtained by regressing $X_{it+4}^{(4)}$ on variables dated *t* and earlier using the forecasting regression,

$$X_{it+4}^{(4)} = \mu_i + \beta_i'\hat{F}_t + \sum_{j=0}^{p-1} a_{ij}\hat{e}_{it-j} + \text{error}, \tag{10}$$

For comparability of results across series, p = 4 lags of $\hat{e}_{it}$ were used for all forecasts.

5.1 The Number and Stability of the Factors

Estimates of the number of factors. Table 1 presents estimates of the number of factors, computed using criteria proposed by Bai and Ng (2002), for the full sample and the two subsamples. The results are not sharp and depend on which criterion is used. For the purposes of forecasting, 10 factors (the estimate suggested using *ICP3*) introduces a large number of parameters in the forecasting regressions so we focus on numbers of factors towards the lower end of the range in Table 1, three to five factors.

Comparison of full-sample and subsample estimated factors. Theorem 1 suggests that, despite possible time variation in the factor loadings, full- and subsample estimates of the factors could well be close, in the sense that the subsample estimates of the factor space is nearly spanned by the full-sample estimate of the factor space. This possibility is examined in Table 2, which presents the squared canonical correlations, computed over the two subsamples, between the factors estimated over the full sample and the factors estimated over the subsample. Canonical correlations close to one indicate that the full-sample and subsample factors span nearly the same spaces.

The results in Table 2 are consistent with there being four full sample factors and three or four factors in each subsample. If there were only two full and subsample factors (as suggested by the ICP2 results in Table 1), then one would expect the third and fourth estimated factors to have little relation to each other over the two subsamples (they would be noise), so the third canonical correlation would be low in both samples. But this is not the case, suggesting that there are at least three factors in each subsample. When four factors are estimated in both the full sample and the subsamples, the fourth canonical correlation is small in the first sample; this is consistent with the space of three first subsample factors being spanned by the four full-sample factors, and the fourth subsample factor being noise. The moderate fourth canonical correlation in the case of four full and four subsample factors leads to some ambiguity, and raises the possibility that there are four factors in the second subsample, which in turn would be consistent with four factors in the full sample.

We interpret the results in Tables 1 and 2, taken together, as being consistent with there being four factors in the full sample and three (or possibly four) factors in each subsample. The large squared canonical correlations in Table 2 for four full-sample and three subsample factors indicate that the full-sample estimated factors span the space of the three estimated factors in each subsample.

5.2 Stability of Factor Loadings and Forecasting Regression Coefficients

Stability of factor loadings. The stability of the factor loadings are examined in the first numeric column Table 3, which reports Chow statistics testing stability of the factor loadings across the two subsamples, computed using the Newey-West (1987) variance estimator (four lags). There is evidence of some instability in the factor loadings: 38% of these Chow statistics reject at the 5% significance level, and 19% reject at the 1% significance level. If one compares the results across classes of series, there are relatively fewer rejections of the stability of the factor loadings for output, employment, and inflation series, and relatively more for series that could be thought of as expectational series such as exchange rates, term spreads, and stock returns.

Figures 1-4 examine the stability of the estimated factors and the factor loadings for four series: real GDP growth, temporally aggregated to be the four-quarter average of the quarterly growth rates (Figure 1); the change in core PCE inflation, temporally aggregated to be the four-quarter change in inflation (Figure 2); the quarterly change in the Federal Funds rate (not temporally aggregated, Figure 3); and the term spread between the one-year and 3-month Treasury rates (not temporally aggregated, Figure 4). Part (a) of each figure presents the series, the common component computed using factors estimated from the full sample with split-sample estimates of the factor loadings (the “full-split” estimate), and the common component computed using split-sample estimates of the factors and split-sample estimates of the factor loadings (“split-split”). Part (b) presents the series, the full-split estimate of the common component, and the common component computed using factors estimated from the full sample and full-sample estimates of the factor loadings (“full-full”).

In all four figures, the full-split and split-split common components (part (a)) are quite similar, consistent with the full-sample factor estimates spanning the spaces of the subsample factor estimates. There are, however, two different patterns evident in part (b) of the figures. For GDP, core PCE, and the Federal Funds rate, the full-split and full-full are similar, indicating that for those series there is little time variation in the factor loadings. This is consistent with the failure of the Chow statistic to reject the hypothesis of stable Λ's for those three series in Table 3. In contrast, stability of the factor loadings is rejected at the 1% significance level for the term spread, and the common components computed using the full-sample factors differ greatly depending on whether the factor loadings are estimated over the full sample or the subsample.

Stability of forecasting regressions. The remaining numeric columns of Table 1 examine the stability of the coefficients in the forecasting regression (10). There is considerably more evidence for instability in the forecasting regression than in the factor loadings themselves: 81% of the Chow statistics testing the stability of all the coefficients in (10) reject at the 5% significance level, and 71% reject at the 1% significance level. If we focus on the coefficients on the factors in the forecasting regression, there is again widespread evidence of instability (68% rejections at the 5% level, 45% rejections at the 1% level), although there is also evidence of considerable instability in the idiosyncratic dynamics.

The fact that there are strikingly more rejections of stability of the coefficients on $\hat{F}_t$ in the forecasting regressions than in the contemporaneous (factor-loading) regressions is consistent with the dynamics of the factor process changing between the two subsamples, see (7).

5.3 Subsample v. Full-Sample Forecasting Regressions

We now turn to a comparison of three different direct four-quarter ahead forecasting methods: full-full (full-sample estimates of the factors, full-sample estimates of the forecasting regression (10)), full-split (full-sample estimates of the factors, split-sample estimates of (10)), and split-split (split-sample estimates of the factors, split-sample estimates of (10)). The results comparing these three methods are summarized in Table 4, for the case of four factors estimated in the full sample and three in each subsample. Of particular interest are the relative MSEs of the three different methods, which are presented in the third and fourth column of the table for the pre-84 sample and in the seventh and eighth column for the post-84 sample.

Inspection of Table 4 reveals two general findings. First, in many cases the relative MSEs comparing the full-split forecasts to the full-full forecasts are substantially less than one, indicating that there are substantial improvements for many series if the regression coefficients are allowed to change between the two subsamples. This is consistent with the many rejections of subsample stability of the forecasting regression coefficients found in Table 3.

Second, the relative MSEs comparing the split-split to full-full forecasts are generally similar to those comparing the full-split to full-full forecasts. That is, there seems to be no systematic advantage to using the subsample estimates of the factors over the full sample estimates, as long as one allows for a break in the forecasting regression coefficients. These two findings, taken together, are consistent with there being breaks in the forecasting regression coefficients, but with the full-sample factors spanning the space of the subsample factors.

As mentioned above, there is ambiguity concerning the number of factors, and the results in Table 4 were repeated for various numbers of full-sample factors and subsample factors (specifically, 4 and 4, 5 and 4, and 5 and 5, respectively). The two general findings stated above are robust to these changes in the estimated factors. The results 4 and 4, 5 and 4, and 5 and 5 factors, like those in Table 4 for 4 and 3 factors, are also consistent with the full-sample factor estimates spanning the space of the subsample factor estimates, but the predictive regressions having coefficients which are unstable across subsamples.

6. Discussion and Conclusions

Several caveats are in order concerning the empirical results. The empirical investigation has focused on the single-break model, and multiple or continuous breaks have been ignored. The break date, 1984, has been treated as known *a-priori*, however it was chosen because of a number of interesting macroeconomic transitions that have been noticed around that date and thus should be thought of as estimated (although not on the basis of breaks in a factor model). The forecasting regressions examined here are all in-sample estimates and might not reflect out-of-sample performance. Finally, the theorem in Section 3 only states that the space of the factors will be consistently estimated, and it does not formally justify the application of the Bai-Ng (2002) criteria or the use of the factors as regressors (existing proofs of these have time-invariant factor loadings, cf. Bai and Ng [2005]).

Despite these caveats, the results suggest several interesting conclusions. The empirical pattern of time variation in the factor loadings is consistent with there being time variation in the process driving the factors. As discussed in Section 3, if a fraction of the variables have a structural break in Λ, principal components will still span the factor space, a prediction that seems to be borne out by the large canonical correlations between the full-sample and subsample estimates of the factors. Consistent with the discussion in Section 2 (see (7)), there is widespread instability in the forecasting equations, in particular many series for which the factor loadings appear to be stable still have unstable forecasting regressions. Accordingly, full-sample estimates of the factors can be used for forecasting (indeed, they might be preferable to subsample estimates, which could have more sampling error), but they should be used in conjunction with subsample, or time-varying, estimates of coefficients in the forecasting regressions.

Appendix A: Data

Table A.1 lists the short name of each series, its mnemonic (the series label used in the source database), the transformation applied to the series, and a brief data description. All series are from the Global Insights Basic Economics Database, unless the source is listed (in parentheses) as TCB (The Conference Board's Indicators Database) or AC (author's calculation based on Global Insights or TCB data). The binary entry in Table A.1 the column labeled "E.F.?" indicates whether that variable was used to estimate the factors. For series available monthly, quarterly values were computed by averaging (in native units) the monthly values over the quarter. There are no missing observations.

The transformation codes in the second column of Table A.1 are defined in the following table, along with the *h*-period ahead version of the variable used in the direct forecasting regressions. In this table, Y_{it} denotes the original (native) untransformed quarterly series.

Code	Transformation (X_{it})	*h*-quarter ahead variable $X_{it}^{(h)}$
1	$X_{it} = Y_{it}$	$X_{it}^{(h)} = Y_{it+h}$
2	$X_{it} = \Delta Y_{it}$	$X_{it}^{(h)} = Y_{it+h} - Y_{it}$
3	$X_{it} = \Delta^2 Y_{it}$	$X_{it}^{(h)} = h^{-1}\sum_{j=1}^{h} \Delta Y_{i,t+h-j} - \Delta Y_{it}$
4	$X_{it} = \ln Y_{it}$	$X_{it}^{(h)} = \ln Y_{it+h}$
5	$X_{it} = \Delta \ln Y_{it}$	$X_{it}^{(h)} = \ln Y_{it+h} - \ln Y_{it}$
6	$X_{it} = \Delta^2 \ln Y_{it}$	$X_{it}^{(h)} = h^{-1}\sum_{j=1}^{h} \Delta \ln Y_{i,t+h-j} - \Delta \ln Y_{it}$

Table A.1 Data sources, transformations, and definitions

Short name	mnemonic	Trans. Code	E.F.?	Description
RGDP	GDP251	5	0	Real Gross Domestic Product, Quantity Index (2000=100) , SAAR
Cons	GDP252	5	0	Real Personal Consumption Expenditures, Quantity Index (2000=100) , SAAR
Cons-Dur	GDP253	5	1	Real Personal Consumption Expenditures - Durable Goods , Quantity Index (2000=
Cons-NonDur	GDP254	5	1	Real Personal Consumption Expenditures - Nondurable Goods, Quantity Index (200
Cons-Serv	GDP255	5	1	Real Personal Consumption Expenditures - Services, Quantity Index (2000=100) ,
GPDInv	GDP256	5	0	Real Gross Private Domestic Investment, Quantity Index (2000=100) , SAAR
FixedInv	GDP257	5	0	Real Gross Private Domestic Investment - Fixed Investment, Quantity Index (200
NonResInv	GDP258	5	0	Real Gross Private Domestic Investment - Nonresidential , Quantity Index (2000
NonResInv-struct	GDP259	5	1	Real Gross Private Domestic Investment - Nonresidential - Structures, Quantity
NonResInv-Bequip	GDP260	5	1	Real Gross Private Domestic Investment - Nonresidential - Equipment & Software
Res.Inv	GDP261	5	1	Real Gross Private Domestic Investment - Residential, Quantity Index (2000=100
Exports	GDP263	5	1	Real Exports, Quantity Index (2000=100) , SAAR
Imports	GDP264	5	1	Real Imports, Quantity Index (2000=100) , SAAR
Gov	GDP265	5	0	Real Government Consumption Expenditures & Gross Investment, Quantity Index (2
Gov Fed	GDP266	5	1	Real Government Consumption Expenditures & Gross Investment - Federal, Quantit
Gov State/Loc	GDP267	5	1	Real Government Consumption Expenditures & Gross Investment - State & local, Q
IP: total	IPS10	5	0	INDUSTRIAL PRODUCTION INDEX - TOTAL INDEX
IP: products	IPS11	5	0	INDUSTRIAL PRODUCTION INDEX - PRODUCTS, TOTAL
IP: final prod	IPS299	5	0	INDUSTRIAL PRODUCTION INDEX - FINAL PRODUCTS
IP: cons gds	IPS12	5	0	INDUSTRIAL PRODUCTION INDEX - CONSUMER GOODS
IP: cons dble	IPS13	5	1	INDUSTRIAL PRODUCTION INDEX - DURABLE CONSUMER GOODS
iIP:cons nondble	IPS18	5	1	INDUSTRIAL PRODUCTION INDEX - NONDURABLE CONSUMER GOODS
IP:bus eqpt	IPS25	5	1	INDUSTRIAL PRODUCTION INDEX - BUSINESS EQUIPMENT
IP: matls	IPS32	5	0	INDUSTRIAL PRODUCTION INDEX - MATERIALS
IP: dble mats	IPS34	5	1	INDUSTRIAL PRODUCTION INDEX - DURABLE GOODS MATERIALS
IP:nondble mats	IPS38	5	1	INDUSTRIAL PRODUCTION INDEX - NONDURABLE GOODS MATERIALS
IP: mfg	IPS43	5	1	INDUSTRIAL PRODUCTION INDEX - MANUFACTURING (SIC)
IP: fuels	IPS306	5	1	INDUSTRIAL PRODUCTION INDEX - FUELS
NAPM prodn	PMP	1	1	NAPM PRODUCTION INDEX (PERCENT)
Capacity Util	UTL11	1	1	CAPACITY UTILIZATION - MANUFACTURING (SIC)
Emp: total	CES002	5	0	EMPLOYEES, NONFARM - TOTAL PRIVATE
Emp: gds prod	CES003	5	0	EMPLOYEES, NONFARM - GOODS-PRODUCING
Emp: mining	CES006	5	1	EMPLOYEES, NONFARM - MINING
Emp: const	CES011	5	1	EMPLOYEES, NONFARM - CONSTRUCTION
Emp: mfg	CES015	5	0	EMPLOYEES, NONFARM - MFG
Emp: dble gds	CES017	5	1	EMPLOYEES, NONFARM - DURABLE GOODS
Emp: nondbles	CES033	5	1	EMPLOYEES, NONFARM - NONDURABLE GOODS
Emp: services	CES046	5	1	EMPLOYEES, NONFARM - SERVICE-PROVIDING
Emp: TTU	CES048	5	1	EMPLOYEES, NONFARM - TRADE, TRANSPORT, UTILITIES
Emp: wholesale	CES049	5	1	EMPLOYEES, NONFARM - WHOLESALE TRADE
Emp: retail	CES053	5	1	EMPLOYEES, NONFARM - RETAIL TRADE
Emp: FIRE	CES088	5	1	EMPLOYEES, NONFARM - FINANCIAL ACTIVITIES

Emp: Govt	CES140	5	1	EMPLOYEES, NONFARM - GOVERNMENT
Help wanted indx	LHEL	2	1	INDEX OF HELP-WANTED ADVERTISING IN NEWSPAPERS (1967=100;SA)
Help wanted/emp	LHELX	2	1	EMPLOYMENT: RATIO; HELP-WANTED ADS:NO. UNEMPLOYED CLF
Emp CPS total	LHEM	5	0	CIVILIAN LABOR FORCE: EMPLOYED, TOTAL (THOUS.,SA)
Emp CPS nonag	LHNAG	5	1	CIVILIAN LABOR FORCE: EMPLOYED, NONAGRIC.INDUSTRIES (THOUS.,SA)
Emp. Hours	LBMNU	5	1	HOURS OF ALL PERSONS: NONFARM BUSINESS SEC (1982=100,SA)
Avg hrs	CES151	1	1	AVG WKLY HOURS, PROD WRKRS, NONFARM - GOODS-PRODUCING
Overtime: mfg	CES155	2	1	AVG WKLY OVERTIME HOURS, PROD WRKRS, NONFARM - MFG
U: all	LHUR	2	1	UNEMPLOYMENT RATE: ALL WORKERS, 16 YEARS & OVER (%,SA)
U: mean duration	LHU680	2	1	UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS (SA)
U < 5 wks	LHU5	5	1	UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5 WKS (THOUS.,SA)
U 5-14 wks	LHU14	5	1	UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS (THOUS.,SA)
U 15+ wks	LHU15	5	1	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS + (THOUS.,SA)
U 15-26 wks	LHU26	5	1	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS (THOUS.,SA)
U 27+ wks	LHU27	5	1	UNEMPLOY.BY DURATION: PERSONS UNEMPL.27 WKS + (THOUS,SA)
HStarts: Total	HSFR	4	0	HOUSING STARTS:NONFARM(1947-58);TOTAL FARM&NONFARM(1959-)(THOUS.,SA
BuildPermits	HSBR	4	0	HOUSING AUTHORIZED: TOTAL new PRIV HOUSING UNITS (THOUS.,SAAR)
HStarts: ne	HSNE	4	1	HOUSING STARTS:NORTHEAST (THOUS.U.)S.A.
HStarts: MW	HSMW	4	1	HOUSING STARTS:MIDWEST(THOUS.U.)S.A.
HStarts: South	HSSOU	4	1	HOUSING STARTS:SOUTH (THOUS.U.)S.A.
HStarts: West	HSWST	4	1	HOUSING STARTS:WEST (THOUS.U.)S.A.
PMI	PMI	1	1	PURCHASING MANAGERS' INDEX (SA)
NAPM new ordrs	PMNO	1	1	NAPM new ORDERS INDEX (PERCENT)
NAPM vendor del	PMDEL	1	1	NAPM VENDOR DELIVERIES INDEX (PERCENT)
NAPM Invent	PMNV	1	1	NAPM INVENTORIES INDEX (PERCENT)
Orders (ConsGoods)	MOCMQ	5	1	new ORDERS (NET) - CONSUMER GOODS & MATERIALS, 1996 DOLLARS (BCI)
Orders (NDCapGoods)	MSONDQ	5	1	new ORDERS, NONDEFENSE CAPITAL GOODS, IN 1996 DOLLARS (BCI)
PGDP	GDP272A	6	0	Gross domestic product Price Index
PCED	GDP273A	6	0	Personal consumption expenditures Price Index
CPI-ALL	CPIAUCSL	6	0	CPI All Items (SA) Fred
PCED-Core	PCEPILFE	6	0	PCE Price Index Less Food and Energy (SA) Fred
CPI-Core	CPILFESL	6	0	CPI Less Food and Energy (SA) Fred
PCED-DUR	GDP274A	6	0	Durable goods Price Index
PCED-DUR-MOTORVEH	GDP274_1	6	1	Motor vehicles and parts Price Index
PCED-DUR-HHEQUIP	GDP274_2	6	1	Furniture and household equipment Price Index
PCED-DUR-OTH	GDP274_3	6	1	Other Price Index
PCED-NDUR	GDP275A	6	0	Nondurable goods Price Index
PCED-NDUR-FOOD	GDP275_1	6	1	Food Price Index
PCED-NDUR-CLTH	GDP275_2	6	1	Clothing and shoes Price Index
PCED-NDUR-ENERGY	GDP275_3	6	1	Gasoline, fuel oil, and other energy goods Price Index
PCED-NDUR-OTH	GDP275_4	6	1	Other Price Index
PCED-SERV	GDP276A	6	0	Services Price Index
PCED-SERV-HOUS	GDP276_1	6	1	Housing Price Index
PCED-SERV-HOUSOP	GDP276_2	6	0	Household operation Price Index

PCED-SERV-H0-ELGAS	GDP276_3	6	1	Electricity and gas Price Index
PCED-SERV-HO-OTH	GDP276_4	6	1	Other household operation Price Index
PCED-SERV-TRAN	GDP276_5	6	1	Transportation Price Index
PCED-SERV-MED	GDP276_6	6	1	Medical care Price Index
PCED-SERV-REC	GDP276_7	6	1	Recreation Price Index
PCED-SERV-OTH	GDP276_8	6	1	Other Price Index
PGPDI	GDP277A	6	0	Gross private domestic investment Price Index
PFI	GDP278A	6	0	Fixed investment Price Index
PFI-NRES	GDP279A	6	0	Nonresidential Price Index
PFI-NRES-STR Price Index	GDP280A	6	1	Structures
PFI-NRES-EQP	GDP281A	6	1	Equipment and software Price Index
PFI-RES	GDP282A	6	1	Residential Price Index
PEXP	GDP284A	6	1	Exports Price Index
PIMP	GDP285A	6	1	Imports Price Index
PGOV	GDP286A	6	0	Government consumption expenditures and gross investment Price Index
PGOV-FED	GDP287A	6	1	Federal Price Index
PGOV-SL	GDP288A	6	1	State and local Price Index
Com: spot price (real)	PSCCOMR	5	1	Real SPOT MARKET PRICE INDEX:BLS & CRB: ALL COMMODITIES(1967=100) (PSCCOM/PCEPILFE)
OilPrice (Real)	PW561R	5	1	PPI Crude (Relative to Core PCE) (pw561/PCEPiLFE)
NAPM com price	PMCP	1	1	NAPM COMMODITY PRICES INDEX (PERCENT)
Real AHE: goods	CES275R	5	0	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - GOODS-PRODUCING (CES275/PI071)
Real AHE: const	CES277R	5	1	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - CONSTRUCTION (CES277/PI071)
Real AHE: mfg	CES278 R	5	1	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - MFG (CES278/PI071)
Labor Prod	LBOUT	5	1	OUTPUT PER HOUR ALL PERSONS: BUSINESS SEC(1982=100,SA)
Real Comp/Hour	LBPUR7	5	1	REAL COMPENSATION PER HOUR,EMPLOYEES:NONFARM BUSINESS(82=100,SA)
Unit Labor Cost	LBLCPU	5	1	UNIT LABOR COST: NONFARM BUSINESS SEC (1982=100,SA)
FedFunds	FYFF	2	1	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA)
3 mo T-bill	FYGM3	2	1	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)
6 mo T-bill	FYGM6	2	0	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA)
1 yr T-bond	FYGT1	2	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)
5 yr T-bond	FYGT5	2	0	INTEREST RATE: U.S.TREASURY CONST MATURITIES,5-YR.(% PER ANN,NSA)
10 yr T-bond	FYGT10	2	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)
Aaabond	FYAAAC	2	0	BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM)
Baa bond	FYBAAC	2	0	BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM)
fygm6-fygm3	SFYGM6	1	1	fygm6-fygm3
fygt1-fygm3	SFYGT1	1	1	fygt1-fygm3
fygt10-fygm3	SFYGT10	1	1	fygt10-fygm3
FYAAAC-Fygt10	SFYAAAC	1	1	FYAAAC-Fygt10
FYBAAC-Fygt10	SFYBAAC	1	1	FYBAAC-Fygt10
M1	FM1	6	1	MONEY STOCK: M1(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL$,SA)
MZM	MZMSL	6	1	MZM (SA) FRB St. Louis
M2	FM2	6	1	MONEY STOCK:M2(M1+O'NITE RPS,EURO$,G/P&B/D MMMFS&SAV&SM TIME DEP(BIL$,
MB	FMFBA	6	1	MONETARY BASE, ADJ for RESERVE REQUIREMENT CHANGES(MIL$,SA)
Reserves tot	FMRRA	6	1	DEPOSITORY INST RESERVES:TOTAL,ADJ for RESERVE REQ CHGS(MIL$,SA)
Reserves nonbor	FMRNBA	6	1	DEPOSITORY INST RESERVES:NONBORROWED,ADJ RES REQ CHGS(MIL$,SA)

BUSLOANS	BUSLOANS	6	1	Commercial and Industrial Loans at All Commercial Banks (FRED) Billions $ (SA)
Cons credit	CCINRV	6	1	CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19)
Ex rate: avg	EXRUS	5	1	UNITED STATES;EFFECTIVE EXCHANGE RATE(MERM)(INDEX NO.)
Ex rate: Switz	EXRSW	5	1	FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.$)
Ex rate: Japan	EXRJAN	5	1	FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$)
Ex rate: UK	EXRUK	5	1	FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)
EX rate: Canada	EXRCAN	5	1	FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$)
S&P 500	FSPCOM	5	1	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)
S&P: indust	FSPIN	5	1	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS (1941-43=10)
S&P div yield	FSDXP	2	1	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)
S&P PE ratio	FSPXE	2	1	S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%,NSA)
DJIA	FSDJ	5	1	COMMON STOCK PRICES: DOW JONES INDUSTRIAL AVERAGE
S&P DivYld	FSDXP	2	1	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)
Consumer expect	HHSNTN	2	1	U. OF MICH. INDEX OF CONSUMER EXPECTATIONS(BCD-83)

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Table 1
Number of Factors Estimated Using Bai-Ng (2002) Criteria

Sample	Dates	No. Obs	Estimated Number of factors based on:		
			ICP1	ICP2	ICP3
Full	1959:III – 2006:IV	190	4	2	10
Pre-84	1959:III – 1983:IV	98	3	2	10
Post-84	1984:I – 2006:IV	92	3	2	10

Notes: All estimates use N = 110 series.

Table 2
Canonical Correlations between Subsample and Full-Sample Estimates of the Factors

Estimated number of factors		Squared canonical correlations between full and subsample factors:									
		Pre-84					Post-84				
Full sample	Subsample	1	2	3	4	5	1	2	3	4	5
3	3	0.999	0.993	0.220			0.992	0.937	0.893		
4	3	0.999	0.994	0.907			0.993	0.945	0.909		
4	4	0.999	0.995	0.947	0.069		0.996	0.950	0.932	0.517	
5	4	0.999	0.995	0.947	0.856		0.996	0.967	0.932	0.741	
5	5	0.999	0.997	0.952	0.905	0.559	0.997	0.975	0.936	0.787	0.236

Notes: The entries are the squared canonical correlations between the estimated factors in the indicated subsample and the factors estimated over the full sample. Factors are estimated using principal components.

Table 3. Chow Statistics Testing the Stability of the Factor Loadings and the 4-Step Ahead Forecasting Equations, 4-Factor Model

Factor loading regression: $X_{it} = \Lambda_i{}'\hat{F}_t + e_{it}$

Forecasting regression: $X^{(4)}_{i,t+4} = \mu_i + \beta_i{}'\hat{F}_t + \sum_{j=0}^{3} a_{ij}\hat{e}_{it-j}$ + error,

where $\hat{F}_t$ are the full-sample factors estimated using principal components, $\hat{e}_{it}$ is the residual from the factor loading regression and $X^{(4)}_{i,t}$ is the 4-quarter variable to be forecast.

Series	**Split-sample Chow statistics testing the stability of:**			
	Factor loadings (Λ_i)	**4-step ahead forecasting regressions:**		
		All coefficients	**coefficients on F_t**	**intercept & coefficients on e_{it-1}**
RGDP	5.5	35.8**	9.4	7.0
Cons	10.7*	54.1**	14.4**	3.3
Cons-Dur	9.4	49.9**	18.2**	3.7
Cons-NonDur	9.8*	19.9*	9.0	6.0
Cons-Serv	4.7	58.8**	12.0*	33.6**
GPDInv	2.0	24.8**	8.7	7.2
FixedInv	6.4	43.0**	24.2**	9.0
NonResInv	4.6	25.3**	19.7**	5.1
NonResInv-struct	5.5	17.5*	11.8*	5.4
NonResInv-Bequip	6.5	43.0**	26.1**	11.1
Res.Inv	3.5	65.0**	10.6*	39.3**
Exports	10.7*	25.0**	3.6	18.9**
Imports	3.7	21.5*	11.2*	3.6
Gov	6.6	8.6	4.0	4.2
Gov Fed	10.7*	7.9	3.9	3.7
Gov State/Loc	5.9	13.1	2.6	11.3*
IP: total	9.8*	31.5**	10.7*	4.5
IP: products	6.0	28.8**	9.4	9.5
IP: final prod	5.0	27.7**	10.1*	9.4
IP: cons gds	8.9	57.6**	14.5**	26.1**
IP: cons dble	9.0	18.1*	6.4	2.8
iIP:cons nondble	4.4	68.1**	18.0**	15.8**
IP:bus eqpt	6.2	31.2**	18.4**	1.8
IP: matls	8.5	26.6**	12.2*	7.2
IP: dble mats	8.6	26.9**	13.4**	11.9*
IP:nondble mats	8.7	63.8**	8.3	26.3**
IP: mfg	9.6*	32.5**	10.8*	4.2
IP: fuels	4.0	9.4	3.3	4.1
NAPM prodn	20.3**	29.4**	4.3	14.4*
Capacity Util	12.2*	35.7**	19.0**	10.1
Emp: total	22.6**	44.1**	18.6**	10.0
Emp: gds prod	18.1**	75.3**	20.6**	20.5**
Emp: mining	2.5	18.7*	8.9	9.5
Emp: const	12.9*	57.7**	43.4**	17.1**

Emp: mfg	23.4**	73.2**	18.0**	22.1**
Emp: dble gds	21.7**	80.6**	22.6**	16.5**
Emp: nondbles	6.9	75.7**	9.9*	56.3**
Emp: services	8.2	50.9**	18.0**	15.3**
Emp: TTU	25.2**	82.3**	33.9**	25.3**
Emp: wholesale	27.0**	77.7**	32.9**	22.0**
Emp: retail	10.4*	174.2**	47.6**	57.5**
Emp: FIRE	13.0*	81.7**	28.6**	39.5**
Emp: Govt	26.1**	28.1**	9.3	22.7**
Help wanted indx	13.8**	51.9**	6.1	26.4**
Help wanted/emp	1.4	23.2**	5.5	11.8*
Emp CPS total	9.9*	25.5**	12.7*	13.1*
Emp CPS nonag	5.0	33.4**	9.5	17.8**
Emp. Hours	25.1**	64.7**	28.6**	8.9
Avg hrs	7.6	85.3**	6.9	65.7**
Overtime: mfg	1.3	16.5	1.4	8.2
U: all	11.1*	25.1**	21.1**	2.3
U: mean duration	4.7	52.6**	13.7**	27.5**
U < 5 wks	15.9**	11.3	8.1	2.5
U 5-14 wks	5.2	15.8	13.5**	1.0
U 15+ wks	2.0	24.0**	16.8**	10.1
U 15-26 wks	3.2	27.8**	13.9**	13.5*
U 27+ wks	0.8	29.0**	14.4**	15.9**
HStarts: Total	9.9*	37.5**	8.9	15.0*
BuildPermits	8.6	26.4**	10.0*	6.7
HStarts: ne	2.0	50.1**	13.9**	26.8**
HStarts: MW	21.7**	18.7*	10.2*	6.7
HStarts: South	16.1**	32.5**	21.3**	9.1
HStarts: West	7.1	28.5**	19.2**	4.8
PMI	24.9**	26.5**	5.3	13.7*
NAPM new ordrs	38.7**	25.8**	3.1	16.4**
NAPM vendor del	14.8**	15.1	8.6	6.4
NAPM Invent	18.1**	69.5**	11.9*	45.4**
Orders (ConsGoods)	11.8*	30.6**	9.5*	12.5*
Orders (NDCapGoods)	6.8	29.7**	16.9**	7.9
PGDP	9.6*	42.2**	34.0**	0.9
PCED	2.0	23.1**	19.5**	3.8
CPI-ALL	6.6	29.7**	23.6**	3.7
PCED-Core	5.3	32.4**	25.1**	6.6
CPI-Core	15.0**	16.4	12.1*	6.3
PCED-DUR	2.2	17.2*	11.9*	2.5
PCED-DUR-MOTORVEH	2.4	8.9	6.3	3.4
PCED-DUR-HHEQUIP	10.0*	68.4**	59.8**	13.2*
PCED-DUR-OTH	3.4	26.5**	13.8**	15.9**
PCED-NDUR	3.0	19.0*	11.1*	2.4
PCED-NDUR-FOOD	5.7	33.7**	22.7**	5.7
PCED-NDUR-CLTH	2.1	12.6	6.3	4.4
PCED-NDUR-ENERGY	7.8	43.6**	27.1**	3.5
PCED-NDUR-OTH	5.3	16.5	1.2	14.8*
PCED-SERV	3.5	65.1**	51.2**	5.0
PCED-SERV-HOUS	2.9	5.4	4.0	2.6
PCED-SERV-HOUSOP	3.2	15.8	11.6*	3.9
PCED-SERV-H0-ELGAS	3.2	13.3	6.7	2.9

PCED-SERV-HO-OTH	3.4	11.9	3.2	6.0
PCED-SERV-TRAN	8.6	77.7**	19.3**	46.0**
PCED-SERV-MED	23.7**	35.8**	13.2*	11.6*
PCED-SERV-REC	6.7	16.2	10.4*	8.1
PCED-SERV-OTH	7.6	22.8**	7.5	6.6
PGPDI	8.2	20.7*	16.1**	3.3
PFI	6.2	27.9**	15.4**	8.6
PFI-NRES	3.6	33.1**	12.4*	20.8**
PFI-NRES-STR Price Index	6.9	15.4	6.2	9.7
PFI-NRES-EQP	1.9	14.2	10.5*	2.1
PFI-RES	4.5	58.1**	20.5**	11.5*
PEXP	5.2	23.8**	11.9*	13.1*
PIMP	4.9	27.3**	16.4**	1.4
PGOV	2.3	21.7*	14.8**	6.0
PGOV-FED	1.4	25.0**	7.6	4.8
PGOV-SL	3.0	25.4**	21.8**	4.3
Com: spot price (real)	7.8	29.4**	14.1**	11.6*
OilPrice (Real)	20.2**	23.3**	12.7*	11.5*
NAPM com price	9.7*	113.6**	21.4**	68.9**
Real AHE: goods	4.2	56.2**	10.6*	36.6**
Real AHE: const	11.3*	38.3**	22.1**	6.9
Real AHE: mfg	7.2	49.2**	8.9	26.0**
Labor Prod	10.5*	7.2	4.7	1.1
Real Comp/Hour	11.3*	11.0	6.3	4.8
Unit Labor Cost	17.4**	47.7**	5.7	41.9**
FedFunds	6.0	41.8**	31.1**	13.6*
3 mo T-bill	3.6	40.7**	29.3**	12.9*
6 mo T-bill	10.3*	32.1**	17.5**	14.0*
1 yr T-bond	9.8*	24.0**	13.1*	13.9*
5 yr T-bond	6.2	11.9	2.2	8.7
10 yr T-bond	5.4	15.0	1.5	8.4
Aaabond	7.6	15.0	4.3	7.1
Baa bond	12.2*	17.0*	7.3	5.8
fygm6-fygm3	22.8**	37.7**	6.8	29.7**
fygt1-fygm3	24.5**	60.1**	29.5**	12.9*
fygt10-fygm3	16.7**	28.4**	11.0*	7.6
FYAAAC-Fygt10	4.9	61.2**	11.9*	35.6**
FYBAAC-Fygt10	12.2*	43.5**	23.2**	11.5*
M1	2.3	10.9	3.2	4.0
MZM	5.2	12.6	6.9	3.9
M2	11.3*	53.9**	42.1**	4.9
MB	9.3	26.8**	11.7*	16.5**
Reserves tot	5.2	43.1**	9.8*	19.0**
Reserves nonbor	8.9	15.3	12.3*	6.0
BUSLOANS	2.8	36.2**	13.9**	10.7
Cons credit	4.6	20.3*	15.8**	2.7
Ex rate: avg	27.4**	23.9**	11.6*	4.5
Ex rate: Switz	10.0*	18.7*	9.0	9.7
Ex rate: Japan	6.1	25.0**	8.5	10.4
Ex rate: UK	6.6	41.9**	13.7**	10.4
EX rate: Canada	5.1	27.7**	19.8**	6.6
S&P 500	9.5	20.4*	11.9*	6.2
S&P: indust	9.3	21.4*	12.9*	5.9

S&P div yield	10.2*	21.8**	15.2**	5.9
S&P PE ratio	18.6**	51.6**	36.6**	6.8
DJIA	6.0	31.4**	13.6**	15.3**
S&P DivYld	10.2*	21.8**	15.2**	5.9
Consumer expect	22.5**	37.5**	18.1**	10.0

Notes: Entries are chi-squared Chow statistics computed using Newey-West (1987) standard errors with 4 lags (column 1) and 5 lags (columns 2-4). Asterisks indicate that the Chow statistics exceed standard *5% and **1% critical values.

Table 4.
Root Mean Square Errors (RMSEs) and Relative MSEs of 4-step ahead Forecasting Regressions: 4 Full-Sample Factors, 3 Subsample Factors

The forecasting regressions (specification (10)) are estimated using:
(a) full-sample factor estimates and full-sample coefficients ("full-full")
(b) full-sample factor estimates and split-sample coefficients ("full-split")
(c) split-sample factor estimates and full-sample coefficients ("split-split")

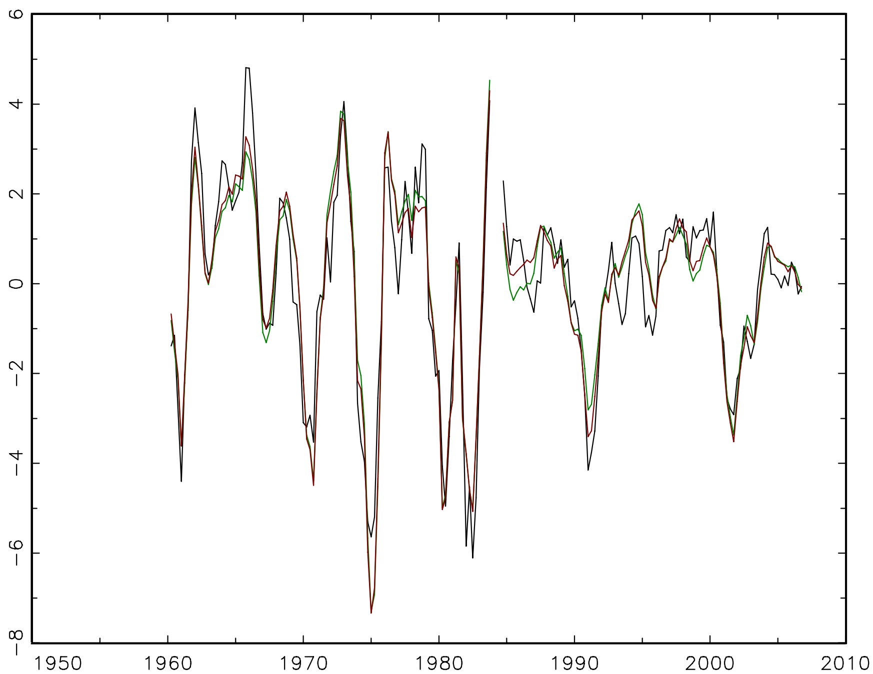
Series (X_{it})	Pre-84 Sample				Post-84 Sample			
	Std dev of $X_{it}^{(4)}$	RMSE, full-full	MSE ratio		Std dev of $X_{it}^{(4)}$	RMSE, full-full	MSE ratio	
			full-split to full-full	split-split to full-full			full-split to full-full	split-split to full-full
RGDP	2.73	2.20	0.94	0.91	1.29	1.22	0.70	0.82
Cons	2.16	1.84	0.96	0.93	1.11	1.09	0.72	0.81
Cons-Dur	7.59	5.83	0.95	0.94	4.42	4.50	0.83	0.86
Cons-NonDur	2.01	1.79	0.90	0.96	1.18	1.17	0.79	0.89
Cons-Serv	1.26	1.19	0.90	0.87	0.86	0.86	0.53	0.66
GPDInv	11.97	8.33	0.90	0.91	6.72	6.22	0.81	0.87
FixedInv	7.85	5.82	0.89	0.89	5.10	4.55	0.70	0.73
NonResInv	7.47	5.43	0.88	0.90	6.14	4.85	0.76	0.75
NonResInv-struct	7.65	6.57	0.87	0.88	7.71	6.18	0.80	0.81
NonResInv-Bequip	8.33	5.85	0.87	0.90	6.09	5.04	0.73	0.74
Res.Inv	16.88	12.26	0.95	0.95	7.25	7.18	0.61	0.73
Exports	6.76	5.30	0.92	0.91	5.27	5.06	0.88	0.89
Imports	8.63	5.84	0.96	0.99	4.56	3.99	0.87	0.92
Gov	2.85	2.48	1.00	1.01	1.77	1.49	0.91	0.92
Gov Fed	5.07	4.34	1.00	1.00	3.54	2.86	0.89	0.86
Gov State/Loc	2.51	2.08	0.99	0.98	1.61	1.35	0.81	0.84
IP: total	5.37	3.75	0.93	0.91	2.80	2.52	0.78	0.82
IP: products	4.58	3.29	0.92	0.90	2.46	2.20	0.74	0.80
IP: final prod	4.50	3.29	0.91	0.90	2.42	2.23	0.73	0.77
IP: cons gds	4.05	2.62	0.95	0.97	1.70	1.91	0.55	0.63
IP: cons dble	9.46	6.75	0.98	0.95	4.80	4.54	0.85	0.91
iIP:cons nondble	2.38	2.04	0.89	0.96	1.40	1.61	0.50	0.62
IP:bus eqpt	8.29	5.31	0.90	0.92	5.88	4.78	0.87	0.88
IP: matls	6.48	4.50	0.94	0.90	3.42	3.21	0.77	0.77
IP: dble mats	9.70	6.52	0.94	0.94	5.52	5.03	0.74	0.77
IP:nondble mats	5.91	4.60	0.86	0.85	2.91	3.18	0.61	0.68
IP: mfg	6.00	4.16	0.93	0.91	3.18	2.80	0.79	0.84
IP: fuels	5.19	5.08	0.96	0.96	3.52	3.40	0.81	0.87
NAPM prodn	8.00	7.15	0.96	0.93	5.56	5.25	0.80	0.96
Capacity Util	5.35	3.09	0.92	0.90	3.19	2.12	0.76	0.84
Emp: total	2.36	1.63	0.90	0.86	1.53	0.98	0.62	0.71
Emp: gds prod	4.20	2.81	0.91	0.88	2.44	1.76	0.59	0.67
Emp: mining	6.69	6.30	0.93	0.94	6.41	5.61	0.82	0.82

Emp: const	5.45	4.06	0.93	0.91	3.89	2.85	0.71	0.77
Emp: mfg	4.26	3.00	0.86	0.84	2.48	2.00	0.50	0.55
Emp: dble gds	5.48	3.78	0.88	0.86	3.11	2.37	0.58	0.61
Emp: nondbles	2.57	2.05	0.75	0.77	1.90	1.44	0.54	0.58
Emp: services	1.33	0.89	0.87	0.85	1.13	0.68	0.70	0.80
Emp: TTU	1.78	1.28	0.81	0.80	1.59	1.06	0.63	0.73
Emp: wholesale	1.88	1.44	0.71	0.73	1.86	1.30	0.71	0.77
Emp: retail	1.74	1.30	0.80	0.79	1.64	1.21	0.58	0.68
Emp: FIRE	1.29	0.89	0.86	0.85	1.63	1.19	0.75	0.83
Emp: Govt	1.93	1.25	0.95	0.95	0.80	0.85	0.65	0.65
Help wanted indx	3.46	2.74	0.84	0.85	2.44	1.85	0.83	0.93
Help wanted/emp	0.09	0.07	0.98	0.97	0.04	0.04	0.72	0.77
Emp CPS total	1.55	1.17	0.86	0.86	0.98	0.78	0.66	0.89
Emp CPS nonag	1.58	1.18	0.85	0.83	1.03	0.82	0.64	0.87
Emp. Hours	2.70	1.95	0.86	0.85	1.98	1.60	0.70	0.75
Avg hrs	0.50	0.36	0.99	0.96	0.42	0.30	0.91	0.91
Overtime: mfg	0.12	0.08	0.93	0.93	0.08	0.07	0.92	0.97
U: all	0.30	0.20	0.96	0.96	0.16	0.12	0.72	0.88
U: mean duration	0.55	0.29	0.93	0.94	0.43	0.25	0.66	0.80
U < 5 wks	9.85	8.23	0.94	0.95	6.50	6.09	0.86	0.94
U 5-14 wks	21.00	15.63	0.97	0.97	11.52	9.49	0.78	0.94
U 15+ wks	38.50	23.83	0.93	0.93	22.77	15.01	0.66	0.77
U 15-26 wks	34.09	22.82	0.94	0.93	19.93	15.12	0.69	0.84
U 27+ wks	46.91	27.26	0.95	0.96	27.70	16.76	0.68	0.83
HStarts: Total	0.23	0.19	0.93	0.95	0.18	0.12	0.78	0.78
BuildPermits	0.26	0.21	0.98	0.97	0.21	0.13	0.77	0.75
HStarts: ne	0.30	0.21	0.96	0.94	0.27	0.16	0.78	0.84
HStarts: MW	0.32	0.25	0.99	0.99	0.14	0.11	0.96	1.04
HStarts: South	0.26	0.19	0.96	0.90	0.23	0.13	0.75	0.79
HStarts: West	0.33	0.24	0.98	1.00	0.20	0.15	0.83	0.86
PMI	7.82	6.90	0.93	0.86	4.66	4.51	0.75	0.91
NAPM new ordrs	8.58	7.54	0.96	0.96	5.85	5.42	0.80	0.98
NAPM vendor del	13.51	11.27	0.95	0.92	4.66	5.09	0.58	0.69
NAPM Invent	7.68	6.51	0.85	0.76	3.15	3.55	0.43	0.51
Orders (ConsGoods)	8.51	6.54	0.88	0.83	3.49	3.60	0.69	0.73
Orders (NDCapGoods)	15.02	11.15	0.91	0.90	9.89	8.52	0.81	0.81
PGDP	1.43	0.99	0.97	0.95	0.73	0.59	0.63	0.71
PCED	1.49	1.16	0.96	0.95	0.99	0.80	0.68	0.76
CPI-ALL	1.98	1.32	0.96	0.96	1.39	1.14	0.71	0.73
PCED-Core	1.24	0.98	0.98	0.99	0.60	0.49	0.59	0.71
CPI-Core	1.99	1.72	0.98	1.02	0.55	0.57	0.52	0.57
PCED-DUR	2.50	1.81	0.95	1.00	1.33	1.25	0.63	0.75
PCED-DUR-MOTORVEH	4.17	2.85	0.98	1.00	2.30	1.87	0.84	0.87
PCED-DUR-	1.92	1.44	0.91	0.98	1.82	1.47	0.59	0.67

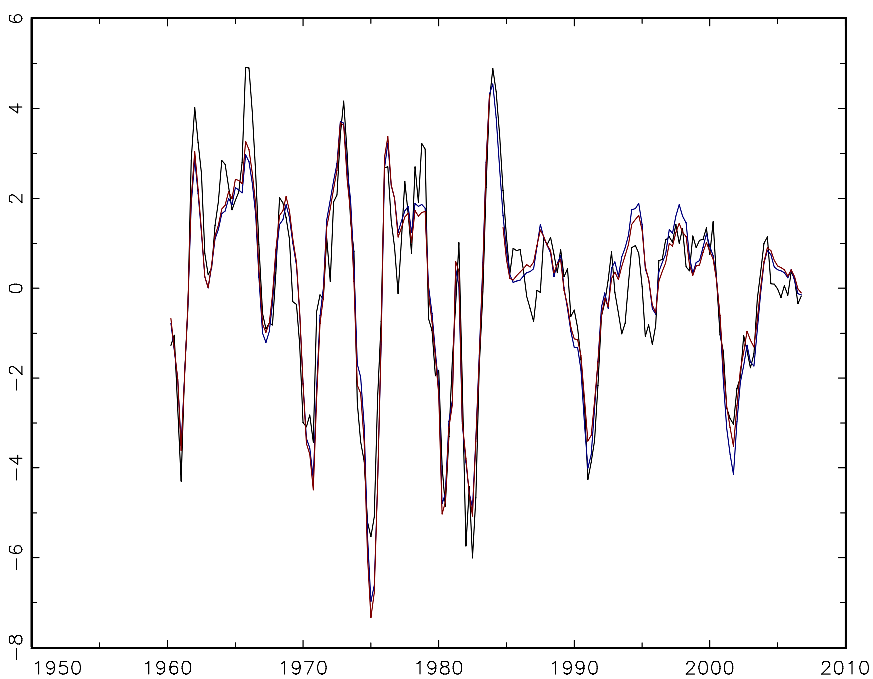
HHEQUIP								
PCED-DUR-OTH	2.87	2.38	0.96	0.96	2.00	1.33	0.71	0.93
PCED-NDUR	2.59	2.00	0.96	0.91	2.95	2.00	0.91	0.94
PCED-NDUR-FOOD	3.28	2.36	1.01	0.98	1.24	0.99	0.76	0.85
PCED-NDUR-CLTH	2.14	1.57	0.93	1.00	3.03	1.78	0.89	0.96
PCED-NDUR-ENERGY	14.29	10.84	0.86	0.85	27.93	18.80	1.02	0.96
PCED-NDUR-OTH	2.49	1.91	0.91	0.94	1.59	1.18	0.77	0.84
PCED-SERV	1.21	0.91	0.98	0.95	0.82	0.56	0.73	0.75
PCED-SERV-HOUS	1.22	0.98	0.98	0.96	0.81	0.63	0.89	0.93
PCED-SERV-HOUSOP	2.40	1.83	0.90	0.89	3.50	2.35	0.91	0.96
PCED-SERV-H0-ELGAS	3.78	2.93	0.68	0.69	7.30	5.89	0.91	0.93
PCED-SERV-HO-OTH	2.74	2.23	0.96	0.98	1.72	1.21	0.74	0.84
PCED-SERV-TRAN	6.80	4.96	0.61	0.63	6.60	7.15	0.71	0.70
PCED-SERV-MED	1.80	1.43	0.94	0.94	0.94	0.96	0.71	0.72
PCED-SERV-REC	1.72	1.12	1.03	1.00	1.10	0.76	0.85	0.95
PCED-SERV-OTH	2.59	2.15	0.95	0.95	2.71	1.97	0.75	0.63
PGPDI	2.63	1.71	0.94	1.01	1.25	1.20	0.54	0.60
PFI	2.66	1.74	0.94	0.99	1.29	1.21	0.55	0.61
PFI-NRES	2.60	1.89	0.91	0.97	1.32	1.23	0.59	0.64
PFI-NRES-STR Price Index	3.68	2.88	0.95	0.97	2.12	1.82	0.73	0.78
PFI-NRES-EQP	2.74	1.92	0.91	0.99	1.62	1.46	0.68	0.71
PFI-RES	4.53	4.11	0.98	0.96	2.21	1.95	0.43	0.44
PEXP	5.17	3.96	0.98	0.92	2.38	2.22	0.70	0.75
PIMP	8.49	7.58	0.95	0.91	6.58	4.87	0.84	0.85
PGOV	2.29	1.33	0.89	0.88	1.62	1.12	0.72	0.72
PGOV-FED	3.89	1.86	0.95	0.95	2.72	1.25	0.86	0.85
PGOV-SL	1.94	1.39	0.89	0.87	1.55	1.28	0.69	0.72
Com: spot price (real)	12.85	10.01	0.87	0.94	9.21	8.56	0.78	0.82
OilPrice (Real)	11.51	11.24	0.71	0.70	24.19	21.98	0.83	0.85
NAPM com price	12.95	11.49	0.84	0.79	13.22	13.49	0.66	0.76
Real AHE: goods	1.49	1.37	0.92	0.97	1.16	0.87	0.74	0.75
Real AHE: const	2.60	1.93	0.98	1.01	1.43	1.20	0.80	0.77
Real AHE: mfg	1.40	1.36	0.89	0.91	1.07	0.93	0.73	0.75
Labor Prod	1.95	1.78	0.97	0.97	1.28	1.16	0.86	0.86

Real Comp/Hour	1.24	1.13	0.93	0.97	1.58	1.54	0.95	0.96
Unit Labor Cost	3.74	2.41	0.99	0.94	1.38	1.55	0.58	0.61
FedFunds	0.63	0.44	0.90	0.87	0.38	0.32	0.67	0.70
3 mo T-bill	0.45	0.33	0.88	0.85	0.35	0.31	0.72	0.74
6 mo T-bill	0.45	0.37	0.89	0.93	0.35	0.31	0.72	0.77
1 yr T-bond	0.46	0.38	0.89	0.95	0.36	0.33	0.78	0.84
5 yr T-bond	0.34	0.31	0.92	0.98	0.30	0.30	0.89	0.83
10 yr T-bond	0.29	0.27	0.91	0.96	0.27	0.27	0.86	0.79
Aaabond	0.26	0.23	0.93	1.00	0.21	0.22	0.86	0.79
Baa bond	0.30	0.26	0.92	0.99	0.21	0.21	0.86	0.80
fygm6-fygm3	0.22	0.21	0.95	0.97	0.14	0.14	0.72	0.80
fygt1-fygm3	0.46	0.40	0.85	0.91	0.31	0.33	0.72	0.77
fygt10-fygm3	1.20	0.92	0.94	0.97	1.12	0.82	0.71	0.70
FYAAAC-Fygt10	0.34	0.30	0.80	0.84	0.40	0.32	0.88	0.91
FYBAAC-Fygt10	0.72	0.48	0.90	0.88	0.50	0.41	0.85	0.88
M1	3.16	2.12	0.89	0.88	4.40	3.74	0.92	0.82
MZM	5.97	5.28	0.96	0.94	5.08	4.57	0.80	0.66
M2	3.09	2.21	0.90	0.92	2.49	2.20	0.71	0.62
MB	1.82	1.43	0.84	0.81	2.94	2.73	0.96	0.94
Reserves tot	5.25	4.03	0.61	0.60	8.64	7.40	0.84	0.83
Reserves nonbor	12.74	12.65	0.78	0.84	14.49	13.00	0.76	0.78
BUSLOANS	6.71	4.92	0.92	0.94	4.91	4.06	0.80	0.86
Cons credit	4.23	3.07	0.87	0.91	3.48	3.35	0.84	0.86
Ex rate: avg	5.00	4.61	0.85	0.83	7.62	7.03	0.89	1.01
Ex rate: Switz	9.70	9.16	0.89	0.93	12.49	11.80	0.88	0.92
Ex rate: Japan	8.71	8.04	0.87	0.97	12.59	11.83	0.92	0.97
Ex rate: UK	9.05	8.30	0.79	0.78	9.12	8.95	0.77	0.95
EX rate: Canada	3.37	3.70	0.74	0.77	5.58	4.56	0.93	0.90
S&P 500	14.28	12.63	0.78	0.82	14.21	14.70	0.75	0.74
S&P: indust	14.66	13.09	0.79	0.83	15.08	15.35	0.77	0.77
S&P div yield	0.17	0.12	0.88	1.03	0.09	0.10	0.62	0.61
S&P PE ratio	0.68	0.54	0.70	0.78	1.27	1.07	0.80	0.81
DJIA	14.09	11.89	0.78	0.80	13.06	13.97	0.67	0.68
S&P DivYld	0.17	0.12	0.88	1.03	0.09	0.10	0.62	0.61
Consumer expect	2.92	2.12	0.83	0.84	2.46	2.53	0.70	0.71

Figure 1. 4-Quarter real GDP growth (black line) and three estimates of its common component: split sample factors, split sample factor loadings (split-split); full sample factors, split sample factor loadings (full-split); and full sample factors, full sample factor loadings (full-full).

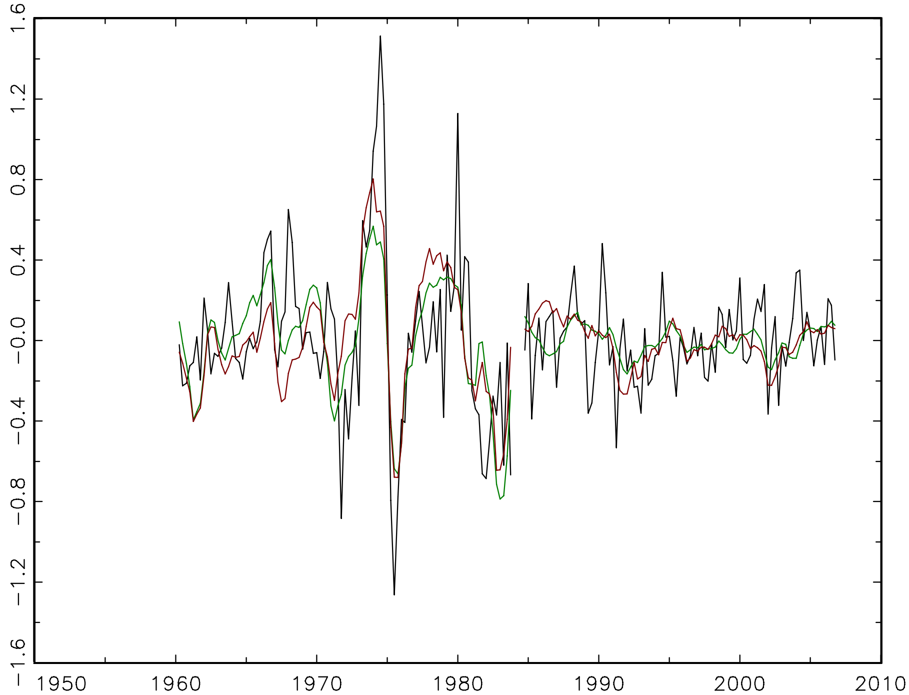


(a) full-split (red) and split-split (green)

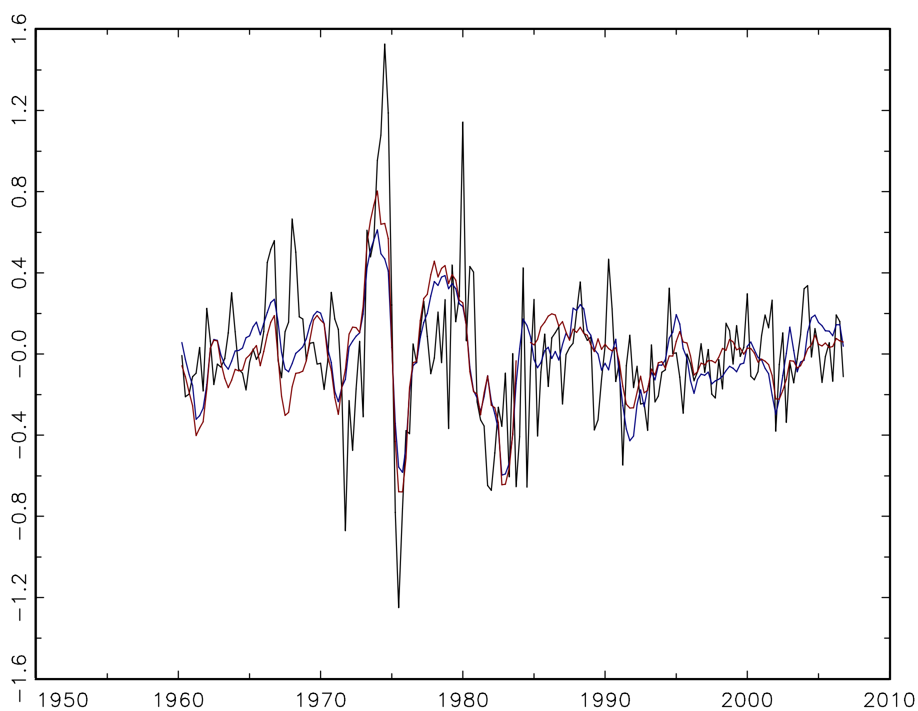


(b) full-split (red) and full-full (blue)

Figure 2. Four-quarter change in core PCE inflation (black line) and three estimates of its common component

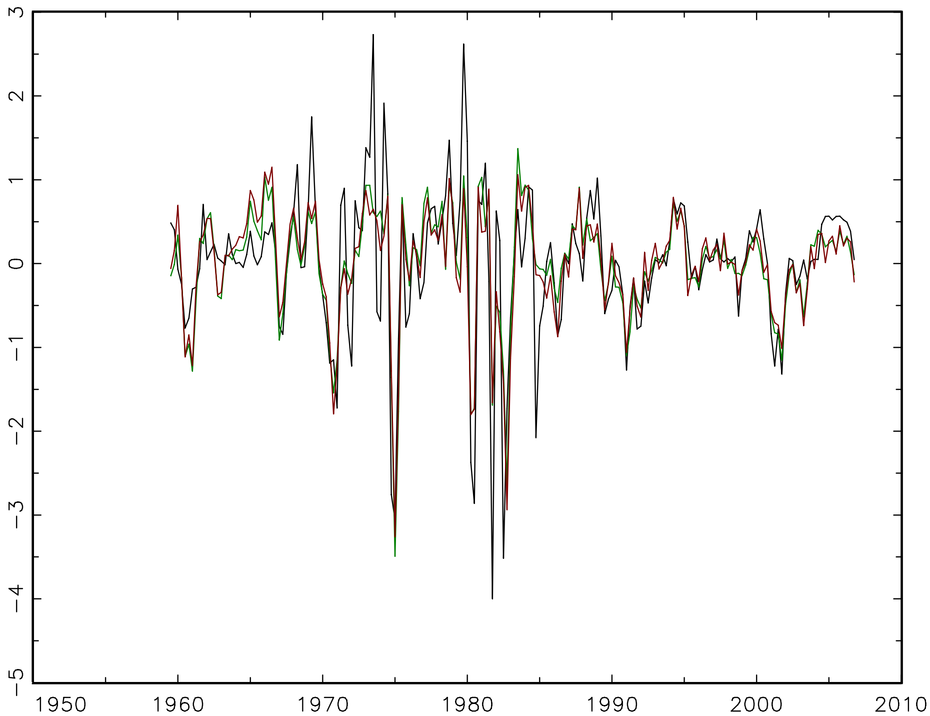


(a) full-split (red) and split-split (green)

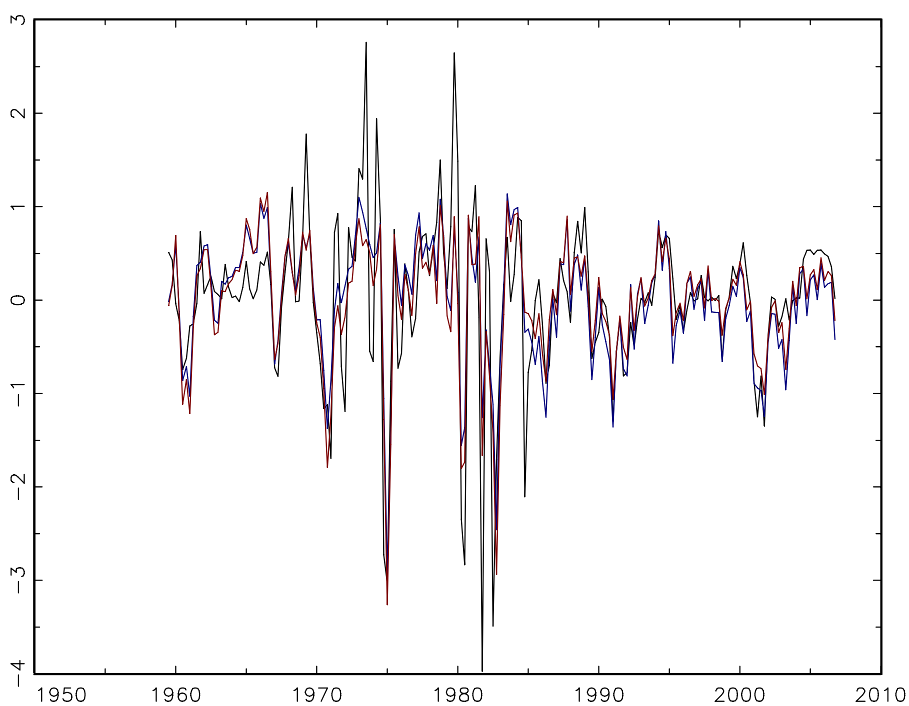


(b) full-split (red) and full-full (blue)

Figure 3. The Federal Funds rate (black line) and three estimates of its common component

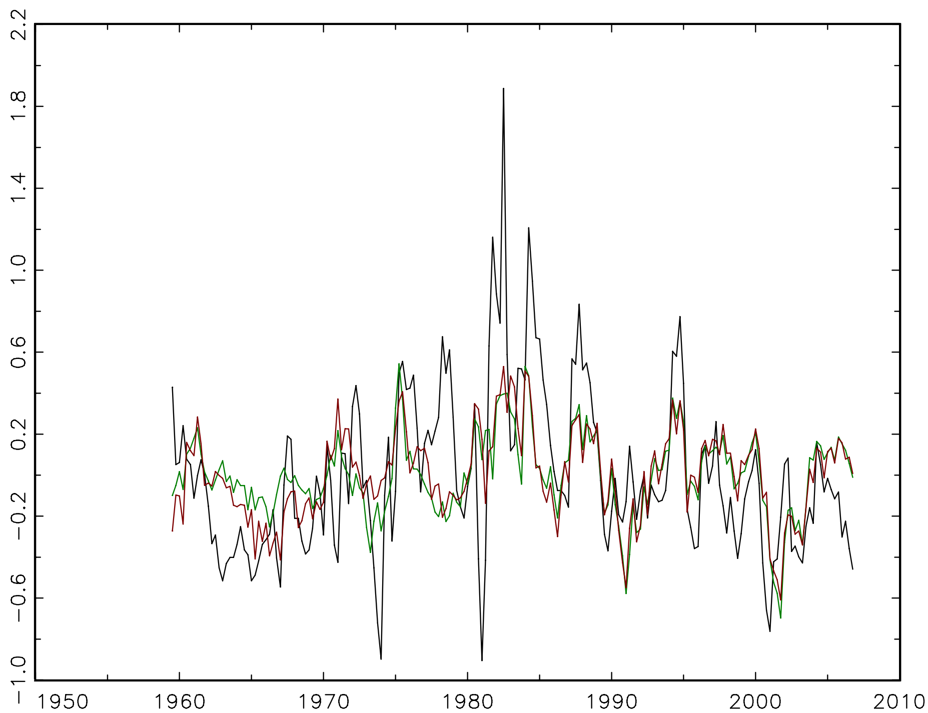


(a) full-split (red) and split-split (green)

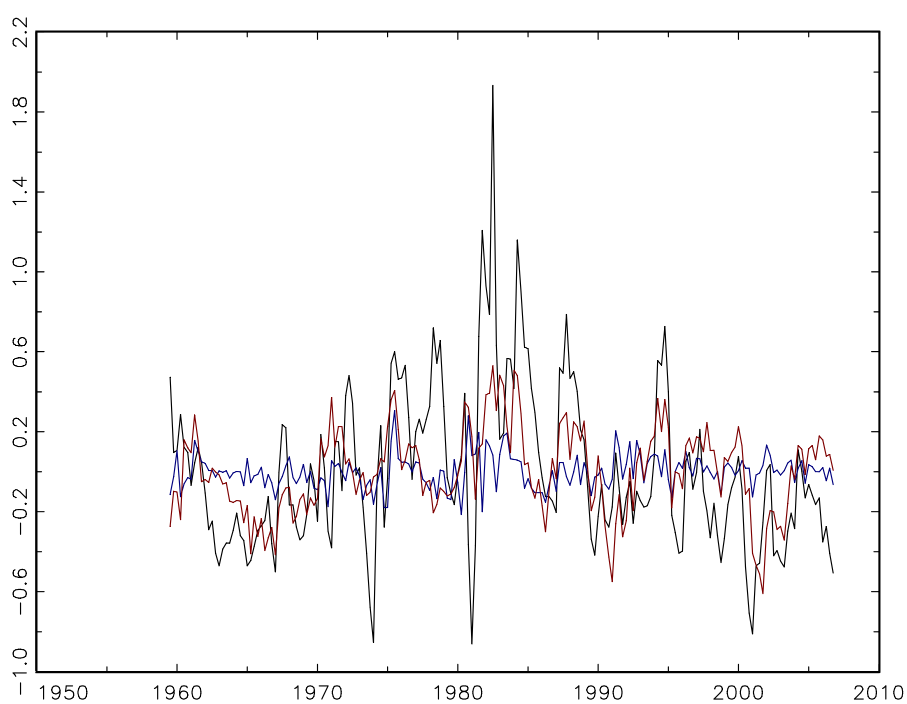


(b) full-split (red) and full-full (blue)

Figure 4 The one-year/3-month Treasury term spread (black line) and three estimates of its common component



(a) full-split (red) and split-split (green)



(b) full-split (red) and full-full (blue)