On the advantages of disaggregated data:
Insights from forecasting the U.S. economy in a data-rich environment

Nikita Perevalov[1] Philipp Maier

Bank of Canada

March 2010

Abstract: The good forecasting performance of factor models has been well documented in the literature. While many studies focus on a very limited set of variables (typically GDP and inflation), this study evaluates forecasting performance at disaggregated levels to examine the source of the improved forecasting accuracy, relative to a simple autoregressive model. We use the latest revision of over 100 U.S. time series over the period 1974-2009 (monthly and quarterly data). We employ restrictions derived from national accounting identities to derive jointly consistent forecasts for the different components of U.S. GDP. In line with previous studies, we find that our factor model yields vastly improved forecasts for U.S. GDP, relative to simple autoregressive benchmark models, but we also conclude that the gains in terms of forecasting accuracy differ substantially between GDP components. As a rule of thumb, the largest improvements in terms of forecasting accuracy are found for relatively more volatile series, with the greatest gains coming from improvements of the forecasts for investment and trade. Consumption forecasts, in contrast, perform only marginally better than a simple AR benchmark model. In addition, we show that for most GDP components, an unrestricted, direct forecast outperforms forecasts subject to national accounting identity restrictions. In contrast, GDP itself is best forecasted as the sum of individual forecasts for GDP components, but the improvement over a direct, unconstrained factor forecast is small.

JEL codes: C50, C53, E37, E47

Keywords: Forecasting; nowcasting; factor model; US economy; US national accounts

---

[1] Corresponding author: Nikita Perevalov, International Department, Bank of Canada, 234 Wellington, Ottawa, ON, K1A 0G9, Email: nperevalov@bankofcanada.ca. We would like to thank Jean Boivin, Sandra Eickmeyer, Larry Schembri, Sharon Kozicki and Nicolas Parent for comments on earlier drafts. The views expressed are of the authors and need not reflect those of the Bank of Canada. All remaining errors are ours.

1 Introduction

Monetary policymakers need up-to-date information to assess the state of the economy and to set interest rates appropriately. The complex nature of monetary policy requires tracking and forecasting numerous variables, including components of national accounts.[2] To forecast a large set of variables, two alternatives are available: first, to have a suite of models, such that key variables can be estimated separately. This allows for more accurate predictions, as each variable can be modelled separately, but a disadvantage is that this approach can be cumbersome and labour-intensive in practice. Also, these forecasts are not necessarily consistent (for instance, when estimated separately, the different components of GDP may or may not add up to the headline number). The second alternative is to forecast all variables jointly. Econometric models can handle large amounts of information, and by extracting "common factors" from time series, these factor models can produce detailed forecasts of many variables in the data set at once.

Past studies have documented the excellent forecasting performance of factor models, and such models have been estimated for many countries. For instance, Stock and Watson (2002) show that factor models outperform univariate autoregressions, small vector autoregressions, and leading indicator models for measures of U.S. output and inflation; Altissimo et al. (2006) develop a factor model to forecast euro area data, and Schumacher (2005)'s factor model for German GDP and Den Reijer (2005)'s model for Dutch GDP both outperform competing AR benchmark models.[3] Factor models also perform well in an environment where data uncertainty is high, as Banerjee et al. (2006) show by using factor models for the new EU members.[4]

Our study builds on these previous studies of factor models, but we add two important elements to the literature. First, first, most studies focus on a relatively limited set of variables (mostly GDP and inflation). We forecast disaggregated data, and show how to adjust the model to yield consistent forecasts, such that forecasts for different components of GDP add up to the total.[5] To this end, we employ restrictions derived

[2] "Fed economists track hundreds, if not thousands, of variables as they prepare for upcoming meetings of the Open Market Committee. Unless the staff economists are wasting their time, one must assume that these hundreds of variables help them isolate the structural shocks currently impacting the economy" (Stock and Watson, 2005).

[3] Other examples are Artis et al. (2004) and Kapetanios (2004) who show that factor models can generate good forecasts for real variables and inflation in the United Kingdom; Matheson (2006) provides an application for New Zealand. Bruneau et al. (2003) and Favero et al. (2004) consider French and Italian inflation, respectively, and Gosselin and Tkacz (2001) predict Canadian inflation with a factor model. Eickmeier and Ziegler (2006) provide a meta-analysis of the forecasting abilities of factor models.

[4] Inoue and Kilian (2005), however, note that substantial forecasting gains can be made with linear regression models, once information from real activity indicators are included, suggesting that some of the gains of factor models in terms of forecasting accuracy could be obtained by simpler forecasting models. Factor models have also been employed to construct factor-augmented VARs, and used to analyze the monetary transmission mechanism (e.g. Bernanke and Boivin, 2003) or the transmission of international shocks (Mumtaz and Surico, 2009).

[5] Forni and Reichlin (1998) also examine disaggregated data, but these authors focus on the number of common shocks driving the U.S. business cycle, not short-term forecasting. Marcellino et al. (2003) consider country-specific vs. area-wide information for the euro area and find that pooling country-wide

from national accounting identities. Second, we use disaggregated data to provide insights as to why factor models are good forecasting tools. We show that not all components of GDP are equally well forecasted and we explore whether the best forecast of GDP is a direct forecast or one where GDP components are first forecasted individually, before they are aggregated to yield the total. Given that real-time data is not readily available for the more than 100 series in our sample, we employ the latest available data.[6]

Over our relatively short forecast horizon (up to 6 months, 2 quarters ahead), our results confirm that factor models outperform simple forecasts based on autoregressive models, including better forecasting performance at turning points. We also find that these forecasting gains are not uniform across components. Broadly speaking, the superior forecasting performance of factor model, relative to AR models, is driven by better forecasting accuracy for relative volatile components of GDP. The factor forecast for consumption, in particular, is not much better than a simple AR process; however, large gains are found for investment and trade data (at some horizons, the forecast errors for subcomponents of investment fall by almost 50 per cent; forecasting errors for imports fall by almost 70 per cent). While the best forecast for GDP components is typically an unrestricted, direct factor forecast, we also conclude that the best forecast for headline GDP is given by the sum of the components forecasts, not a direct GDP forecast (but the difference between the forecasts is small). In combination with adding-up restrictions derived from national accounts, factor models produce fairly accurate, jointly consistent short-term forecasts, while maintaining the ability to provide explanations for observed movements.

The outline of this study is as follows. In the next section we provide some background information on the monetary policy process at the Bank of Canada, and explain the methodology. We report the estimation results in section 3. Section 4 summarized our main findings.

2 Monitoring economic developments at a central bank

2.1 Short-term forecasting at central banks

To assess the state of the economy, many central banks rely on the use of models of various types. At the one end of the spectrum are models based on economic theory (estimated or calibrated) that are well suited to explain the underlying economic forces and transmission mechanisms. At the other end of the spectrum are purely empirical models with a very limited set of theoretical relationships (if any), which can produce accurate forecasts, in particular in the short run.

information yields better forecasts for area-wide aggregates, but they do not consider different GDP components (they focus on total GDP, inflation, industrial production and unemployment).

[6] Data revisions can be substantial, and can affect estimation of forecasting models (such as lag length), as well as measures of forecast errors (see Stark and Croushore, 2002; Kozicki 2001). Real-time data for the United States is available from the Federal Reserve Bank of Philadelphia, but only for a relatively small subset of the series we employ.

A complication is that central banks are typically interested in forecasts for many economic variables, which is quite unlike many academic studies that tend to focus on relatively few variables. Recent econometric advances, including factor models, have the potential to facilitate this task considerably. Exploiting a much richer base of information than is conventionally used for time series forecasting, factor models (also referred to as "forecasting with many predictors") have the potential to streamline the monitoring process, and might even provide some robustness against structural instability, which can affect low-dimensional forecasting (Stock and Watson, 2005).[7]

The usefulness of factor models as a short-term forecasting tool depends on various criteria. Most important is the reliability of short-term forecasts relative to a simple benchmark forecasting model (in our case an autoregressive model), in particular for variables that other models have a hard time explaining, and over periods in which other models do not perform very well. For instance, many empirical, as well as theoretical models find it hard to forecast turning points accurately. Second, as central banks prefer accurate and coherent forecasts of many national accounts series, our focus is not only on getting the best forecast for a single variable, but on generating good forecasts for all key components of the U.S. National Accounts.[8] Third, a successful monitoring tool must be able to handle missing observations, different data frequencies, and use higher-frequency data to inform estimates of lower-frequency time series.[9] As shown below, factor models can produce reliable, short-term forecasts, based on data observed at different frequencies. Also, factor models can deal with unbalanced data sets (also called data with "ragged edges"), which occur when data are released at different points in time.[10]

2.2 Methodology

The traditional, atheoretical method to estimate economic relationships is VAR analysis (Sims, 1980). VAR models capture the evolution and the interdependencies between multiple time series.[11] The advantage of using VARs is that they provide plausible assessments of the dynamic responses of key macroeconomic variables to shocks, without requiring a complete structural model of the economy. A limitation of VAR's, however, is that they tend to become extremely large, as the number of variables

---

[7] It is also possible to integrate high-frequency indicators into structural models, as e.g. outlined in Benes et al. (2009).

[8] This distinguishes our approach from Cheung and Demers (2007), who focus on a smaller subset of variables.

[9] Suppose that we are interested in a forecast for GDP of the current quarter. If we are presently in the third month of this quarter, we would ideally be able to use the information gained in the first two months to inform the forecast for the entire quarter. *In theory*, high-frequency indicators should improve forecasting performance, since the amount of information is greater. *In practice*, however, the effect is not evident, since high-frequency information might harm forecasting performance due to (i) errors introduced from generating missing observations, and (ii) the fact that high-frequency indicators might simply contain noise.

[10] When business cycle indicators are released at different points in time, data becomes unbalanced at the end of multivariate samples ("ragged edge"). Zheng and Rossiter (2006) provide a different approach to update a forecast for data sets with "ragged edges".

[11] In a VAR, all variables are treated symmetrically by including for each variable an equation explaining its evolution based on its own lags and the lags of all other variables in the model.

increases. Factor analysis is a method for summarizing the main sources of variation and covariation among variables. Based on the notion that the covariance (or correlation) structure of the data contains important information, factor analysis reduces the dimensionality of data sets by modeling observed variables as linear combinations of several unobservable "factors" (plus error terms). Previous studies found that in many cases, a small number of factors account for the bulk of the observed variation of major economic aggregates (Sargent and Sims, 1977; Stock and Watson, 1989, 1991; Sargent, 1989). Consequently, a relatively simple forecast for many variables can be obtained by using the estimated dynamic factors, instead of using all series themselves.[12]

We proceed as follows. Our first step is to adopt the method outlined in Stock and Watson (2002), which demonstrates how a simple iterative procedure, based on principal components, can be used to extract a small set of underlying factors from a large set of data. Stock and Watson (2002) also show how to handle practical issues such as mixed data frequencies, missing data and unbalanced data ("ragged edges").[13] Following this approach, we will forecast total GDP, as well as disaggregated GDP components, and examine forecasting accuracy by component. In our second step, we apply restrictions to our disaggregated forecasts to ensure that they are jointly consistent. Given that most studies focus on forecasts for aggregated data, this second step has not been widely applied in the literature.

Formally, the traditional factor model is given by the following. For a vector of data, X, of size n, assume that the underlying structure is as follows:

$$X_t = \Lambda F_t + e_t \tag{3.1}$$

where F is a vector of common factors.[14] If the dataset is balanced, F can simply be estimated by principal components. If the dataset is unbalanced, for example due to missing data, mixed frequency data or a ragged edge, an iterative two-step procedure is required to estimate principal components. Commonly referred to as the expectations-maximization (EM) algorithm (since each iteration of the algorithm consists of an expectation step, followed by maximization, see Dempster et al., 1977), this is accomplished using the following objective function:

$$V(F,\Lambda) = \sum_{i=1}^{N}\sum_{t=1}^{T}(X_{it} - \lambda_i ' F_t)^2, \tag{3.2}$$

where λ_i is the ith row of Λ. If X is balanced, minimizing the objective function, subject to the restriction that $\Lambda'\Lambda$ is the identity matrix, we obtain the matrix of principal components F and the loadings matrix Λ. If the dataset is unbalanced, eq. (3.2) can be modified to yield:

[12] Stock and Watson (2005) show that the performance of estimators of the factors typically improves as the number of series increases.

[13] Breitung and Eickmeier (2005) provide a recent overview of dynamic factor models.

[14] A dynamic factor model can be transformed into this static representation, provided that the dynamic factor model features a finite number of lags.

(3.3) $\tilde{V}(F,\Lambda)=\sum_{i=1}^{N}\sum_{t=1}^{T} I_{it}(X_{it}-\lambda_i{}'F_t)^2$,

with $I_{it}=1$ when X_{it} is available and zero otherwise. To obtain estimates from eq. (3.3), notice that the objective function in eq. (3.2) is proportional to the log-likelihood under the assumption that X is i.i.d. N($\lambda_i{}'F_t$,1). Thus, the least square estimates provide the Gaussian maximum likelihood estimates.

Eq. (3.3) is a missing data version of eq. (3.2), and since it is easier to minimize the latter, we use the following algorithm. Given the estimates of $\hat{F}_{k-1}$ and $\hat{\Delta}_{k-1}$ from iteration (k-1), we minimize

(3.4) $\tilde{V}_k(F,\Lambda)=\sum_{i=1}^{N}\sum_{t=1}^{T}[I_{it}(X_{it}-\lambda_i{}'F_t)^2+(1-I_{it})(E_{\hat{F}_{k-1},\hat{\Delta}_{k-1}}(X_{it}\mid X^{obs})-\lambda_i{}'F_t)^2]$,

where $E_{\hat{F}_{k-1},\hat{\Lambda}_{k-1}}(X_{it}\mid X^{obs})=(\hat{\Lambda}_{k-1}\,\hat{F}_{k-1})_{it}$, when the data for X_{it} is not observed and $E_{\hat{F}_{k-1},\hat{\Lambda}_{k-1}}(X_{it}\mid X^{obs})=X_{it}$ otherwise. By minimizing the objective function in eq. (3.4), we obtain $\hat{F}_k$ and $\hat{\Lambda}_k$. In turn, these estimates are used in iteration *k* to fill in the missing data values. We iterate until convergence.[15]

Having estimated the factors, the quarterly data can be forecasted by estimating each variable as a function of the factors, as well as lagged values of the variable, through the following relationship:

(3.5) $X_{it+h}=\alpha+\beta(L)F_t+\gamma(L)X_{it}+\varepsilon_{t+h}$.

2.3 Data

We use the most latest available data for 136 series, covering the period 1974-2009. Of these series, 115 are available at monthly frequency, and 21 at quarterly frequency (see appendix for a detailed description).[16] The series cover output and income, employment and hours, residential investment, stock prices, exchange rates and a number of others (a complete list is provided in the appendix). The data are transformed, if needed, to ensure stationarity (most series are in log-differences; quarterly data are in growth rates).

To show how informative monthly indicators are for quarterly national accounts data, table A.1 in the appendix shows the distributions of absolute correlations between monthly series and the one quarter lead of different GDP components. As can be seen, monthly data have relatively high information content for total GDP and investment, as the distributions of correlation coefficients are high. In contrast, monthly indicators contain less information for government consumption expenditures and investment, with correlation coefficients distribution concentrated between 0 and 0.9. The same can be

[15] The dimensions of *F* can be determined with information-based tests, such as Bai and Ng (2006).

[16] Ideally, we would conduct a similar exercise with real-time data. Unfortunately, the power of factor models arises from pooling large data sets, and real-time data for such an extensive array of series is not readily available.

said about services exports. Given these characteristics of monthly data, we would expect the factor model to do better at forecasting GDP and investment, and not so well in forecasting government expenditures and some components of trade. In what follows, we check whether this hypothesis is indeed correct.

3 Results

3.1 The Benchmark AR Model

Table 1 shows the volatility of key components of the U.S. national accounts (column 2), as measured by their standard deviation. While GDP and consumption are relatively stable, other components – notably housing and business investment – are more volatile. In addition, there are differences in volatility at a more disaggregated level within components: while consumption of services has the lowest volatility of all series shown in table 1, consumption of durables is more volatile. Similarly, within investment, investment in structures is considerably more volatile than investment in equipment.

To evaluate the forecasting power of the factor model, we compute a benchmark forecasting model, based on simple AR processes for the different variables. Admittedly, an AR process is a benchmark with substantial shortcomings, including its small information set and difficulties at forecasting turning points. However, its simplicity is a major advantage, explaining why this choice of benchmark is very popular in the literature (see, for example, Breitung et al., 2006).

For each variable, the optimal lag length is chosen using the Schwartz criterion (maximum lag length is 3). Then, we conduct out-of-sample forecasts for the next quarter. The third column of table 1 shows the Root Mean Squared Forecast Error (RMSFE) of the benchmark AR model. It is not surprising that the AR model's RMSFEs are larger for relatively more volatile components. For components such as business investment or residential investment, the AR benchmark model produces relatively accurate forecasts. The RMSFEs for residential investment is almost 40 per cent lower than the series' variance; for business investment, the RMSFE is still roughly 20 per cent lower than its variance. The AR model also performs well for consumption, which has by far the largest weight in overall U.S. GDP (close to 70 per cent).

3.2 The Baseline Quarterly Factor Model

The first step to build our factor model is to extract the factors from the set of variables. Consistent with previous studies, we find that a relatively small number of factors is sufficient to explain most of the variation in our dataset. All factor models retain three factors.[17] The first factor extracted in the principal components step is most highly correlated with measures of real output, including manufacturing industrial production, manufacturing purchasing managers index and total nonfarm employment. Other factors are more closely associated with prices – measures of inflation, such as CPI – and monetary policy related variables, in particular federal funds rate and bank reserves.

[17] We retain three factors in the EM step; otherwise the out-of-sample forecasting exercise becomes very computationally intense.

Table 2 compares the forecasting performance of the benchmark AR model to the quarterly and monthly factor models. All columns show the ratio of the mean squared forecast error of the factor models, divided by the benchmark AR. First, we estimate the factor model with quarterly data. This avoids dealing with mixed frequency data, and will later help isolate the benefits of moving to higher frequencies. We use 40 quarters to conduct out-of-sample forecasts.[18] Thus, the initial estimation period is 1974-1999. Each subsequent quarter we extend the estimation period by one and forecast the subsequent out-of-sample time period.

Several observations stand out: first, even with quarterly data, there is a marked improvement over AR models' forecasts for some series, in particular for GDP (column 2). [19] Overall, the mean squared forecast error of GDP forecasts one quarter ahead are over 30 per cent lower for the factor model than for the benchmark AR. Second, these improvements are not found for all series (the AR forecast errors for the consumption component, for instance, are more than 50 per cent smaller than those of the factor model). As a rule of thumb, large improvements are typically witnessed for series that exhibit a relatively high degree of volatility, such as trade data, business investment, or consumption of durables. This finding is driven by the fact that the AR model is not performing well for volatile series, while the factor model is better able to exploit the rich dataset and to provide reasonably good forecasts for these volatile series (see table A.2 at the back for details). An important caveat, however, is that the baseline factor model is performing considerably worse for some series, including consumption of services, housing investment and final domestic demand. It therefore seems that the improvements in forecasting accuracy are not exclusively driven by the degree of volatility of the underlying series.

3.3 The Monthly Factor Model

Next, we add monthly data and estimate a mixed frequency model. Comparing the baseline model to the mixed frequency model indicates the degree to which forecasting performance improves by including monthly data. We expect forecasting performance to increase substantially, as we provide the model with more information (in addition, this allows us to generate monthly observations for data that is only available at quarterly frequencies, such as GDP). For the remaining columns of Table 2, we use 120 months of data, from 2000 to 2009, to compute out-of-sample forecasts. Each month a forecast is made for the first subsequent quarter-end. Each time the data is included up to and including the forecast month.

[18]The number of time periods used in the EM step should be at least as great as the number of series (136), in order to have a non-singular variance matrix. This limits the size of the initial sample, from which we iterate in the out-of-sample forecast exercise.

[19] The statistical significance is assessed using the test described in Diebold and Mariano (1995).

Table 1: The forecasting performance of the benchmark AR deteriorates if data is very volatile (criterion: RMSFE; AR lag length based on Schwartz criterion)

	Standard deviation (in %)	AR RMSFE for period Q+1
Consumption	2.16	1.85
Consumption: services	1.85	1.94
Consumption: non-durables	5.68	5.66
Consumption: durables	9.76	10.44
Residential Investment	16.44	10.04
Business Investment	10.77	8.76
Business Investment: Equipment	10.53	9.61
Business Investment: Structures	15.81	12.99
Final Domestic Demand	3.19	2.08
Exports	10.96	14.14
Imports	10.44	11.53
GDP	2.90	2.78

Note: These out-of-sample forecasts were computed over 40 quarters (1999-2009).

We observe a marked improvement for most series in the monthly factor model, relative to the AR and the forecasts of the quarterly model.[20] In particular, the forecast errors for GDP are more than 40 per cent below the forecast errors of the AR model and are below the quarterly factor model's errors. Also, incorporating higher-frequency data reduces the forecast error for consumption to levels comparable to the benchmark AR model. Note, however that there does not seem to be an obvious relationship between the data volatility and the improvements from the incorporation of higher-frequency data. While most of the series are better forecasted by the monthly model, consumption of services remains an area where the AR model has an advantage.

At the longer horizon, the factor model retains better forecasting accuracy for most series, but the advantage is decreasing. For example, forecasting GDP 6 months in advance with the factor model under consideration is about as effective as using an AR model (similarly, Eickmeier and Ziegler, 2006, find that factor models seem to be better suited to predict output at shorter forecast horizons than at longer horizons). However, as the quarter's end approaches, more information is revealed, and the factor model's forecast improves rapidly. Overall, the quarterly factor model outperforms the simple AR for most series, except total consumption, housing investment and business investment in structures.

[20] Similar findings are reported for euro area data in Barhoumi et al. (2008).

Table 2: The quarterly factor model and the mixed frequency factor model outperform the AR model (criterion: ratio of factor model MSFE, divided by MSFE of the AR model)

	Quarterly factor model	Mixed frequency factor model					
Factor Model/AR MSFEs	Quarter Q+1	Quarter Q+1, *ends in months*			Quarter Q+2, *ends in months*		
		3	*2*	*1*	*6*	*5*	*4*
Consumption	2.180	0.94	0.99	1.03	1.03	1.14	1.15
Services	2.641	0.89**	1.44	1.45	0.98	1.23	1.21
Non-durables	0.859*	0.96	0.68**	0.72**	0.92*	0.96	0.98
Durables	0.816	0.94	0.98	0.92	1.06	0.96	1.02
Residential Investment	2.230	0.94	1.74	1.69	1.05	1.25	1.26
Business Investment	0.527*	0.52**	0.58*	0.81	0.79*	0.58**	0.47*
Equipment	0.653**	0.51**	0.51**	0.62**	0.85	0.61**	0.49**
Structures	1.080	0.93**	1.28	1.39	0.96	0.83	0.88
Final Domestic Demand	2.229	0.71*	0.89	0.89	1.04	0.85	0.87
Exports	0.846*	0.85*	0.56**	0.50**	1.01	0.89	0.88
Imports	0.326**	0.26**	0.24**	0.31**	0.60**	0.46**	0.39**
GDP	0.628**	0.61**	0.53**	0.66**	0.85	0.78	0.66*

Ratio of MSFE from the factor model to the AR. Note: The forecasts from the baseline factor model are calculated for the full quarter for 6,5,4,3, 2 and 1 months in advance. Numbers less than one are highlighted in grey. The factor model significantly outperforms the AR at the 5% (**) and 10% (*) level.

Next, we consider the models' performance at turning points. We consider the following periods: 2001Q1, 2001Q3, 2008Q1, 2008Q3-2009Q2. Since the AR model only incorporates information that is lagged at least one quarter, we expect the factor model to be more accurate than the benchmark AR model in forecasting during these periods. This is indeed the case (see table 3). The overall mean squared forecast error of factor model's output forecasts during turning points is almost 80 per cent lower than those of the AR model. In all cases, the factor model performs better at a turning point, as forecasts three months before the quarter's end are already significantly more accurate than the AR model. For instance, for 2001, the factor model does not forecast negative growth in any of the quarters, but it does suggest growth rates close to zero. The AR model, in contrast, significantly overpredicts output growth for all quarters (not only in 2001, but in 2008-2009 as well). For the same periods, the forecast errors of the factor model are about 25 per cent lower than those of the AR model.

Figure 1 illustrates the forecast accuracy of the mixed frequency factor model for GDP. As can be seen, the factor forecast clearly outperforms the AR forecast, notably during recessions. The most important benefit can be seen in 2008, as the factor model signalled as early as July 2008 very weak and eventually negative growth, helped by "early warning" from monthly indicators. Note, however, that the advantage of the factor model over a simple AR model is much less obvious when looking at consumption (figure 2). Since 2007, both the AR model and the factor model have had difficulties in predicting the large fall in consumption.

Table 3: The quarterly factor model performs better during turning points (MSFE of the monthly factor model, divided by the MSFE of the AR model, during turning points)

	Relative MSFE
Consumption	0.74
Residential Investment	1.50
Nonresidential Investment	0.48
Final Domestic Demand	0.51
Exports	0.69
Imports	0.20
GDP	0.23

MSFE of the monthly factor model, divided by the MSFE of the AR model, during turning points. Numbers less than one are highlighted in grey.

Figure 1: The factor model forecasts GDP better than the benchmark AR, including turning points

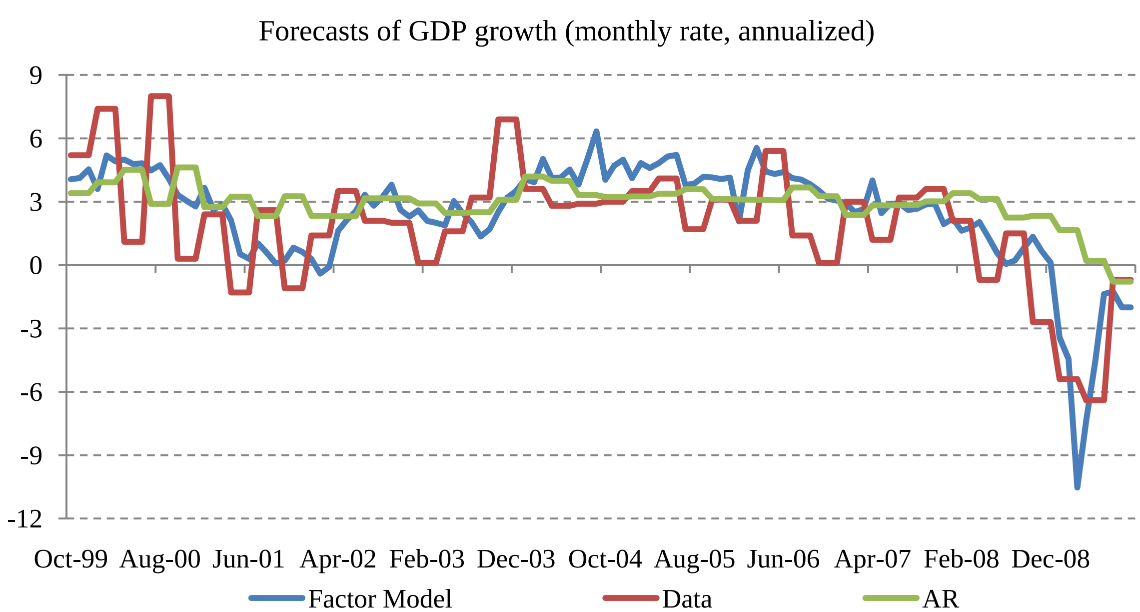
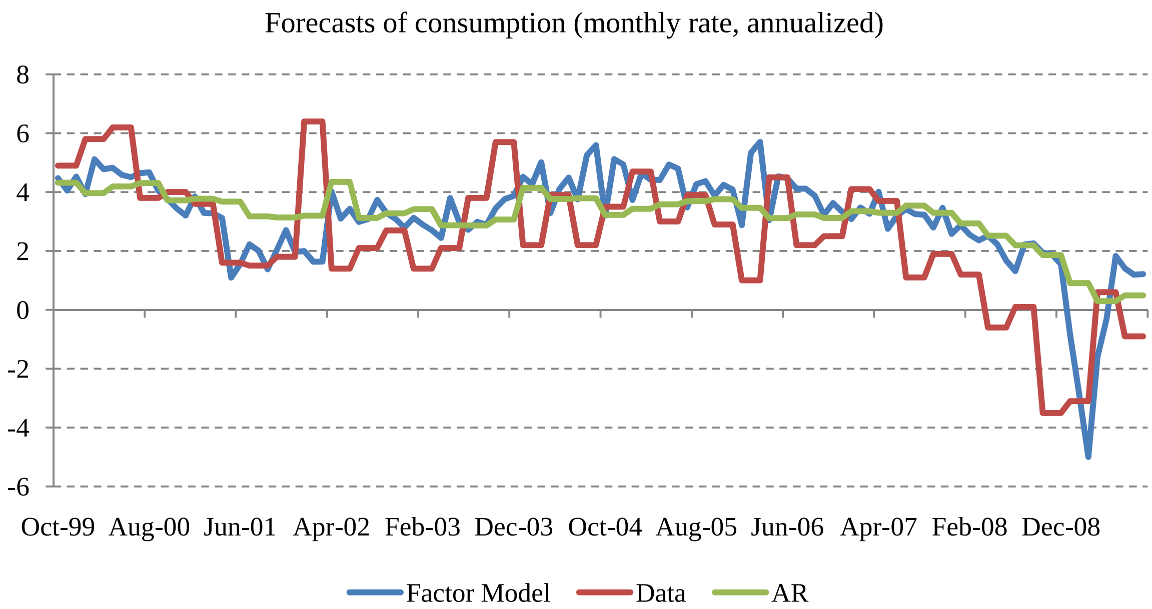


Figure 2: Forecasting accuracy of the factor model is not substantially better than the benchmark AR for consumption



3.4 Comparing direct forecasts to aggregated forecasts of GDP components

So far, our results confirmed that the quarterly factor model's forecasts are not only more accurate (on average) than the AR benchmark, but the model also has a substantial advantage at identifying turning points. In what follows, we examine the sources of these forecasting gains in more detail, and also augment the model to ensure that all forecasted series are jointly consistent. The first issue we tackle is whether the best GDP forecast is a direct forecast (that is, forecasted directly using the factor model), or one in which all GDP components are forecasted separately, and then added up.

There are two main reasons why in our framework the direct forecast can differ from the sum of forecasted components. First, the data might exhibit an aggregation bias. If GDP components are measured imperfectly and contain a measurement error, then the aggregate – the sum – could compound these errors (Theil, 1954). Second, when generating forecasts for GDP components by using eq. (3.5), we use lagged values of the component. This implies that even if the same factors are used to generate forecasts for components, they still use different lagged values.[21] Hence, by comparing the direct forecast and the aggregated sum of component forecasts, we can check whether a direct forecast is preferable because it avoids the aggregation bias, or whether disaggregation helps because the model is uses different information to generate a component forecast.

To this end, using the data in contributions to GDP growth, we generate forecasts by predicting each component of GDP independently, and comparing it to a forecast

[21] In addition, for some components, we also use a different factor, as for all component forecasts, we select the three factors that exhibit the highest correlation with the left-hand side variable.

generated as a sum of subcomponents. The results are reported in table 4 (as before we compare the factor model to the benchmark AR model).

Table 4: GDP best forecasted as sum of components, GDP components best forecasted individually (monthly factor model forecasts MSFEs, divided by MSFEs of the AR model)

		Quarter Q+1 ends in months		
Index or Formula		3	2	1
1+6+14+17+20	**GDP (sum of components)**	0.57**	0.13**	0.67**
	GDP (direct forecast)	0.61**	0.53**	0.74**
3+4+5	**Consumption (sum of components)**	0.91	0.63	0.96
1	**Consumption (direct forecast)**	0.94	0.93	0.97
2	Goods	0.99	0.86	0.87
3	Durable goods	0.98	1.01	0.98
4	Nondurable goods	0.94	0.67**	0.70**
5	Services	0.77**	1.08	1.14
9+10+11+12	**Investment (sum of components)**	0.43**	0.17**	0.63*
6	**Investment (direct forecast)**	0.42*	0.33**	0.46**
7	Fixed investment	0.56*	0.56**	0.88
8	Nonresidential investment	0.48**	0.58**	0.85*
9	Structures	0.99	1.26	1.4
10	Equipment and software	0.54**	0.51**	0.69**
11	Residential investment	0.79**	1.97	1.90
12	Change in private inventories	0.92	0.94	1.05
13	Net exports of goods and services	0.81*	0.91	0.95
15+16	**Exports (sum of components)**	0.92	0.57**	0.73**
14	**Exports (direct forecast)**	0.82**	0.76**	0.75**
15	Goods	0.86*	0.75**	0.72*
16	Services	0.77**	0.63**	0.62**
18+19	**Imports (sum of components)**	0.65*	0.49**	0.75**
17	**Imports (direct forecast)**	0.60*	0.61**	0.72**
18	Goods	0.60*	0.60**	0.69**
19	Services	1.01	0.98	0.97
20	**Government expenditures**	0.99	0.95	0.93*

All data in contributions to GDP growth. Monthly factor model forecasts MSFEs, divided by MSFEs of the AR model. Factor model outperforms the AR at a 5% (**) and 10% (*) level of significance. Numbers less than one are highlighted in grey.

We focus on two issues:

- Examining which components of GDP tentatively can be said to drive the improvements in forecasting accuracy, relative to the benchmark AR;
- Comparing forecasts of a variable based on summing its subcomponents (bottom-up) to a direct, unrestricted forecast of the variable itself.

As regards the first issue, table 4 shows very clearly that the large gains in terms of forecasting accuracy are found in the investment component. Fixed investment, investment in equipment and software, and imports and exports, in particular, are much better forecasted by the monthly factor model than the benchmark AR. At the beginning of the quarter, the forecasting performance of the factor model is also considerably superior to the benchmark AR for consumption of services and residential investment, but these advantages diminish, as more information becomes available during the quarter (in fact, for both subcomponents, the AR forecasts eventually perform better than the factor model). Improvements in consumption forecasts are more modest, although it seems that non-durable goods consumption is forecasted considerably better with a factor model. Taken together, this suggests that the factor model's higher accuracy in forecasting GDP is explained by accuracy of investment forecasts (at least measured against our benchmark AR model).

As regards the second issue, forecasts for GDP (and, to a certain extent, consumption), yield higher forecasting accuracy when calculated as the sum of their subcomponents than a direct forecast, but the differences are small.[22] All other GDP components, in contrast, are better forecasted directly, as the forecast based on the sum of subcomponents performs slightly worse than the direct forecast. This suggests that within GDP components, forecasts calculated as sum of sub-components compound errors, whereas there is sufficient variation at the component level to "average out" errors for the headline GDP forecast. An inspection of the forecast errors confirms this hypothesis: while the correlation of forecast errors within the consumption component of GDP is generally fairly small (less than 0.15), the correlation of forecast errors for investment in structures and investment in equipment is relatively large (0.4, see Table 5).[23]

This large positive correlation implies that if the forecast for one subcomponent of investment is too strong or too weak, the forecast of the other component is similarly incorrect. Hence, investment is best forecasted directly. In contrast, the correlation of the forecast errors for the different components of GDP is smaller, and negative (Table 6). Consequently, GDP is best forecasted as the sum of the components, because the forecast errors "even out".

[22] Table 4 expresses the forecasts relative to the AR benchmark model, but as the benchmark is the same for the direct forecast and the forecast based on the sum, it is also true that the forecast of the sum yields is simply more accurate for consumption and investment.

[23] This suggests that the reason why Marcellino et al. (2003) find that pooling country-wide information yields better forecasts for euro area-wide aggregates could be due to country-specific errors cancelling out (rather than being compounded).

Table 5: Forecast errors for investment are more positively correlated than forecast errors for consumption

Correlation of forecast errors: Consumption		
	Durables	Nondurables
Nondurables	0.11	
Services	0.15	0.15
Correlation of forecast errors: Investment		
	Structures	Equipment
Equipment	0.4	
Residential investment	-0.1	0.12

Table 6: Forecast errors for major GDP components likely "even out"

Correlation of forecast errors	Consumption	Investment	Exports	Imports
Investment	-0.1889			
Exports	-0.0267	0.2033		
Imports	-0.0187	-0.371	-0.7295	
Government	-0.0189	0.2989	0.0667	-0.0649

3.5 Adding restrictions to ensure joint consistency

A drawback of the FAVAR employed above is that forecasts for each series are generated independently. National accounting implies many restrictions on economic series, and as the model is missing this (additional) information, the series may or may not add up. This limits the usefulness of factor forecasts in explaining economic developments at the disaggregated level. In table 4, we simply aggregated forecasts of individual components, a better way to achieve consistency is by incorporating restrictions from national accounts *directly* when estimating forecast regressions.

Possible restrictions include that components of GDP, such as consumption, investment, net exports and government expenditures, add up to the total. However, these constraints can be taken a step further: Consumption, for instance, can be expressed as the sum of consumption of durable goods, non-durable goods, and services.[24] Separate regressions for each of these subcomponents do not account for the fact that the three components must sum to the total.[25] In our particular case, "adding-up" restrictions will mean growth of total consumption should be the sum of contributions to growth coming from the three subcomponents. Ways to incorporate such restrictions are explored in the literature on

[24] A drawback is that this reasoning cannot be applied to all variables in our data set. For instance, there is no obvious restriction for variables such as wage costs. However, since our main focus is on components in U.S. national accounts, this drawback seems acceptable.

[25] A similar idea has been explored by Moench (2008), who uses a factor model to forecast the yield curve, and imposes no-arbitrage conditions.

fully restricted regressions.[26] The first step of extracting factors from a panel of data with mixed frequencies remains identical (employing the EM algorithm). However, when individual regressions are run to compute forecasts for the series of interest, we impose joint adding up restrictions as in Haupt and Oberhofer (2002). These have the following form:

(4.1) $A'*Y = 0$, where

(4.2) $Y = X\beta + u$,

and X is a matrix of regressors. This translates into the following restrictions on the coefficients and residuals, given predetermined regressors:

(4.2) $(A'*X)\beta = 0$

(4.3) $A'*u = 0$

For this approach to yield correct estimates, these calculations are performed in contributions to growth, not growth rates.

The first step is to see how the model with restrictions performs, relative to the unrestricted model. Table 7 contains mean squared forecast errors for major GDP components of the restricted model, relative to the unrestricted monthly factor model. In this case, we only imposed one restriction: the growth rates of consumption, investment, exports, imports, and government all have to add up to the growth rate of overall GDP.[27] As seen, adding restrictions does not substantially deteriorate the accuracy of the "headline" GDP forecast (differences are not statistically significant). As regards to individual GDP components, the forecasting performance even improves for exports (the improvement is significant at 5 per cent level three months before the quarter's end), but worsens slightly for other components, notably early in the quarter (but note that the forecasting performance improves for almost all variables, relative to the benchmark monthly factor model, as more information becomes available during the quarter). This suggests that the consistency of GDP forecasts comes at the "expense" of somewhat worse forecasts for some GDP components.

[26] Fully restricted regression refers to the situation when not only the coefficients, but the dependent variables themselves are subject to restrictions. Among other things, this means the residuals' variance-covariance matrix is singular.

[27] Investment includes inventories.

Table 7: National accounting restrictions hardly change forecasting accuracy for total GDP (MSFE of the restricted monthly factor model, divided by the unrestricted monthly factor model, for GDP components in terms of contributions to growth)

	3	2	1
GDP	1.00	1.00	1.00
Consumption	1.06	1.01	0.96
Investment	0.99	1.03	1.05
Exports	0.90**	1.01	1.00
Imports	1.10	0.98	0.98
Government	0.95	1.00	1.00

Numbers less than one are highlighted in grey.

Table 8: Imposing restrictions improves subcomponent forecasts (MSFE of the restricted monthly factor model, divided by the MSFE of the unrestricted monthly factor model)

		Quarter Q+1, ends in months		
		3	*2*	*1*
Q/Q Growth	Consumption	1.10	0.99	0.97*
Contribution to growth	Services consumption	1.38	0.98**	0.97**
	Nondurable consumption	0.91**	0.99	0.98*
	Durable consumption	0.99	1.01	0.98

Restricted Model is superior at 5% (**), 10% (*).Numbers less than one are highlighted in grey.

Table 9: Decomposition of the restricted forecast for consumption in 2009Q2

Forecasts		*May*	*June*
Q/Q Growth, 2009Q2	Consumption	0.87%	0.73%
Contribution to growth	Services consumption	1.10%	0.95%
	Nondurable consumption	-0.04%	-0.07%
	Durable consumption	-0.18%	-0.15%
Total	Contribution to growth	0.87%	0.73%

While the benefits in terms of consistency from imposing national accounting restrictions accrues for all GDP components, not all components benefit from improved forecasting accuracy. Table 10 shows the forecast for total business investment and the two sub-components “Investment in structures” and “Investment in equipment and software”. As can be seen, forecasting accuracy for the subcomponent “Equipment” improves slightly, while the forecasts for total and structures investment worsen slightly (but none of the differences are statistically significant. This suggests that the unrestricted factor model is slightly better at using all available information to forecast total investment, while imposing national accounting restrictions seems to compound forecasting errors for subcomponents. This suggests that imposing restrictions is not useful when the subcomponents are not particularly well forecasted, or when the forecasting errors of the subcomponents are highly correlated.

Table 10: Imposing restrictions worsens the forecast for investment (MSFE of the restricted monthly factor model, divided by the MSFE of the unrestricted monthly factor model)

		Quarter Q+1, ends in months		
		3	*2*	*1*
Q/Q Growth, 2009Q2	Business Investment	1.09	1.02	1.08
Contribution to growth	Structures	1.23	1.01	0.98
	Equipment	0.96	0.98	0.99

Numbers less than one are highlighted in grey.

4 Conclusion

Developing short-term forecasts for an economy involves processing large volumes of data. To facilitate this task, factor models are a useful tool. While previous studies have documented the usefulness of factors models and their excellent forecasting abilities for selected variables – notably GDP and inflation – the exact reasons why factor models outperform simple benchmark models have not been thoroughly explored.

We construct a factor model for U.S. data and examine forecast accuracy at the disaggregated level. In line with previous studies, we find that the model's forecasting accuracy is superior to simple autoregressive models, in particular when higher-frequency data is incorporated. Also, factor models yield better forecasting performance at turning points. However, these gains are not found for all components of GDP. As a rule of thumb, we find that factor models can yield substantial improvements for relatively more volatile series, such as investment, while only very small gains are found for consumption. We also examine various ways to forecast GDP, and find that the differences between a direct, unconstrained forecast and a forecast based on aggregating GDP components are relatively small.

One issue that arises when making forecasts for GDP components is that forecasts should be jointly consistent (that is, that the components add up to the total). To this end, we impose restrictions on the behavior of aggregate series in order to ensure that accounting identities are satisfied. As we show, these restrictions force the model to produce jointly consistent forecasts for all series, and forecasting performance suffers very little, relative to an unconstrained forecast. One implication of imposing national accounting restrictions is that when forecast errors for subcomponents are highly correlated, a forecast based on the sum of the subcomponent essentially compounds the forecasting errors. In contrast, when forecasting errors are uncorrelated, the sum of the components might outperform a direct factor forecast, since the errors even out.

Overall, we conclude that the main reason why factor models yield good forecasts is because of relatively high forecast accuracy for volatile GDP components. In combination with national accounting restrictions, factor models have the potential to develop good and consistent short-term forecasts, while maintaining the ability to interpret economic developments. From a practical perspective, an important advantage of factor models is also that one model can generate forecasts for all series in the sample, greatly facilitating the labor-intensive tasks of building forecasting models for each series individually.

Looking ahead, we envisage two extensions. First, to exploit fully the benefits of jointly consistent forecasts from factor models, we will investigate incorporating additional national accounting restrictions in future analysis. Second, as mentioned earlier, real-time data is not readily available for the more than 100 time series (spanning a period of more than 30 years) in our sample. However, it might be worthwhile to conduct a similar exercise for a reduced, real-time data set, as it would not only allow forecasting in real-time, it would also provide various ways to calculate the potential for data revisions. This is clearly an important issue for future research.

5 References

Altissimo, F., Cristadoro, R., Forni, M., Lippi, M., Veronese, G., 2006. New EuroCOIN: Tracking Economic Growth in Real Time, CEPR Discussion Papers 5633.

Artis, M., Banerjee, A, Marcellino, M., 2004, Factor Forecasts for the UK, Journal of Forecasting, 24(4), 279-298.

Bai, J., Ng, S., 2006, Evaluating latent and observed factors in macroeconomics and finance, Journal of Econometrics, 131 (1-2), 507-53.

Banerjee, A., Marcellino, M., Masten, I., 2006, Forecasting macroeconomic variables for the new member states, in: Artis, M., Banerjee, A., Marcellino, M. (eds.), The Central and Eastern European countries and the European Union, Cambridge University Press, Cambridge, Chapter 4, 108-134.

Barhoumi, K., Benk, S., Cristadoro, R., Den Reijer, A., Jakaitiene, A., Jelonek, P, Rua, A., Rünstler, G., Ruth, K., Van Nieuwenhuyze, C., 2008, Short-term forecasting of GDP using large monthly datasets: A pseudo real-time forecast evaluation exercise, ECB Occasional Paper Series, 84.

Benes, J., Clinton, K., Johnson, M., Laxton, D. and T. Matheson, 2009, Structural models in real time, *mimeo (International Monetary Fund).*

Bernanke, B., Boivin, J., 2003, Monetary policy in a data-rich environment, Journal of Monetary Economics 50, 525–546.

Breitung, J., Eickmeier, S., 2005, Dynamic factor models, Deutsche Bundesbank Discussion Paper Series 1, 38.

Breitung, J., Schumacher, C., 2006, Real-time forecasting of GDP based on a large factor model with monthly and quarterly data, Deutsche Bundesbank Discussion Paper Series 1, 33.

Bruneau, C., de Bandt, O., Flageollet, A., Michaux E., 2003, Forecasting inflation using economic indicators: The case of France, Banque de France NER 101.

Chung, C., Demers, F., 2007, Evaluating Forecasts from Factor Models for Canadian GDP Growth and Core Inflation, Bank of Canada Working Paper 2007-8.

A. Dempster, N. Laird and D. Rubin, 1977, Maximum Likelihood from Incomplete Data via the EM Algorithm, Journal of the Royal Statistical Society, Series B (Methodological), 39(1), pp. 1-3.

Diebold, F.X. and Mariano, R.S., 1995. Comparing predictive accuracy. Journal of Business and Economic Statistics 13, pp. 253–263.

Den Reijer, A., 2005, Forecasting Dutch GDP using large scale factor models, DNB Working Paper, 28.

Eickmeier, S., Ziegler, C., 2006, How good are dynamic factor models at forecasting output and inflation? A meta-analytic approach, Deutsche Bundesbank Discussion Paper Series 1, 42.

Favero, C., Ricchi, O., Tegami, C., 2004, Forecasting Italian inflation with large datasets and many models", IGIER Working Paper 269.

Forni, M., Giannone, D., Lippi, M., Reichlin, L., 2007, Opening the black box: Structural factor models with large cross-sections, ECB Working Paper 712.

Forni, M., Reichlin, L., 1998, Let's get real: A dynamic factor analytical approach to disaggregated business cycle dynamics, Review of Economic Studies 65, 453-473.

Gosselin, M. and G. Tkacz, 2001, Evaluating Factor Models: An Application to Forecasting Inflation in Canada, Bank of Canada Working Paper 18.

Haupt, H., Oberhofer, W., 2002, Fully restricted regression: A pedagogical note, Economics Bulletin.

Inoue, A., Kilian, L., 2005, How useful is bagging in forecasting economic time series? A case study of US CPI inflation, CEPR Discussion Paper 5304.

Kapetanios, G., 2004, A note on modelling core inflation for the UK using a new dynamic factor estimation method and a large disaggregated price index dataset, Economics Letters, 85, 63-69.

Kozicki, S., 2001, Implications of real-time data for forecasting and modeling expectations, Federal Reserve Bank of Kansas City Research Working Paper 01-12.

Marcellino, M., Schumacher, C., 2008, Factor-MIDAS for now- and forecasting with ragged-edge data: A model comparison for German GDP, CEPR Workin Paper 6708.

Marcellino, M., Stock, J., Watson, M., 2003, Macroeconomic forecasting in the euro are: Country-specific versus area-wide information, European Economic Review, 47(1), 1-18.

Matheson, T., 2006, Factor model forecasts for New Zealand, International Journal of Central Banking, 2, 169-237.

Mumtaz, H., Surico, P., 2009, The Transmission of International Shocks: A Factor-Augmented VAR Approach, Journal of Money, Credit and Banking, 41 (1), 71-100.

Moench, E., 2008, Forecasting the yield curve in a data-rich environment: A no-arbitrage factor-augmented VAR approach, Journal of Econometrics 146, 26-43.

Sargent, T., 1989, Two models of measurements and the investment accelerator, The Journal of Political Economy, 97(2), 251-287.

Sargent, T., Sims, C., 1977, Business cycle modeling without pretending to have too much a priori economic theory, in C. Sims (ed.), New Methods in Business Research, Federal Reserve Bank of Minneapolis.

Schumacher, C., 2005, Forecasting German GDP using alternative factor models based on large datasets, Deutsche Bundesbank Discussion Paper 24/2005.

Stark, T., Croushor, D., 2002, Forecasting with a real-time data set for macroeconomists, Journal of Macroeconomics, 24 (4), 507-531.

Stock, J., Watson, M., 2002, Macroeconomic Forecasting Using Diffusion Indexes, Journal of Business and Economic Statistics, Vol. 20 (2).

Stock, J., Watson, M., 2005, Implications of Dynamic Factor Models for VAR Analysis, NBER Working Paper Series, 11467.

Theil, H., 1954, Linear Aggregation of Economic Relations, Amsterdam, North-Holland.

Yi Zhen, I., Rossiter, J., 2006, Using Monthly Indicators to Predict Quarterly GDP, Bank of Canada Working Paper 2006-26.

6 Appendix

Our data set comprises the following series for 1974-2009:

Real Output and Income:

1. Industrial Production:

Products, Total
Final Products
Consumer Goods
Dur. Cons. Goods
NonDur. Cons. Goods
Business Equip.
Materials
Dur. Goods Materials
NonDur. Goods Materials
Manufacturing
Dur. Manufact.
NonDur. Manufact.
Mining
Utilities
Total Index

2. Capacity Utilization Rate:

Manufact. Total

3. Others:

Purchasing Managers Index
NAPM Production Index
Personal Income

Employment and Hours:

1. Help Wanted Index:

Advertising in Newspapers
Ratio: Help-wanted Ads

2. Civilian Labor Force:

Employed, Total
Employed: NonAgr. Indust

3. Unemployment Rate:

All Workers 16 yrs & Over
Avg. Duration weeks
Pers. Unemploy. < 5 weeks
Pers. Unemploy. 5 to 14 wks
Pers. Unemploy. 15 wks +
Pers. Unemploy. 15 to 26wks

4. Employees on NonAgr. Payrolls:

Total
Total, Private
Goods-Producing

4. Employees on NonAgr. Payrolls, contd.:

Mining
Contract Construct.
Manufacturing
Durable Goods
Nondurable Goods
Service Producing
Trans. & Public Util.
Wholesale & Retail
Finance, Ins. & Real. Est.
Services
Government

5. Average Weekly Hours of Production Workers:

Manufacturing
Mfg. Overtime
NAPM Employment Index

Housing Starts & Sales:

Non-Farm Total
Northeast
MidWest
South
West
Total New Priv. Housing
Mobile Homes

Real Inventories, Orders & Unfilled Orders

NAPM Inventories Index
NAPM New Orders Index
NAPM Deliveries Index

New Orders:

Consumer Goods & Mat.
Nondef. Capital Goods

Common Stock Price Index: S&P

Composite
Industrials
Dividend Yield
Price/Earnings Ratio

Foreign Exchange Rates, to USD:
Switzerland
Japan
United Kingdom
Canada

Interest Rates:
Federal Funds
Treasury Bills 3-mo.
Treasury Bills 6-mo.
Treasury Bills 1-yr.
Treasury Bills 5-yr.
Treasury Bills 10-yr.
Moody's AAA Corp.
Moody's BAA Corp.
Spread 3-mo. vs Fed Funds
Spread 6-mo. vs Fed Funds
Spread 1-yr. vs Fed Funds
Spread 5-yr. vs Fed Funds
Spread 10-yr. vs Fed Funds
Spread AAA vs Fed Funds
Spread BAA vs Fed Funds

Money and Credit Quantity Aggregates
Money Stock: M1
Money Stock: M2

Monetary Base:
Adj. for Res. Req. Chge.

Depository Institutions' Reserves:
Tot. Adj. for Res. Req. Chge.
Nonbor. Adj. Res. Req. Chge
Comm. & Ind. Loans Out.
Net Chge Comm. & Ind. Lns.
Consumer Credit Outstand.

Price Indexes:
1. NAPM:
Commod. Prices Index
2. Producer Price Index:
Finished Goods
Finished Consumer Goods
Intermed. Mat. Sup. & Conp.
Crude Materials
CORE PPI
3. C.P.I.
All Items
Apparel & upkeep
Transportation
Medical Care
Commodities
Durables
Services
All items less Food
All Items less Shelter
All Items less Med. Care
Core CPI
Core PCE

Average Hourly Earnings:
Constr. Workers: Construct.
Prod. Workers: Manufact.

Miscellaneous:
U of Mich. Index Cons. Confid. Expect.

Exports:
Total
Indust. Supp. & Mat.
Capital Gds. Excl. MV&P
Motor Vehicle & Parts
Other Merchandise

Imports:
Total
Indust. Supp. & Mat.
Capital Gds. Excl. MV&P
Motor Vehicle & Parts
Other Merchandise

Table A.1. Distribution of absolute correlation coefficients of the target variable one quarter ahead and monthly data.

	5th percentile	median	95th percentile
Gross domestic product	0.0258	0.2239	0.5753
Personal consumption expenditures	0.0264	0.248	0.4887
Goods	0.0178	0.2343	0.479
Durable goods	0.0134	0.2141	0.4213
Nondurable goods	0.0088	0.2031	0.4474
Services	0.0136	0.2134	0.4902
Gross private domestic investment	0.0202	0.1788	0.5524
Fixed investment	0.0137	0.2276	0.6025
Nonresidential	0.0242	0.1934	0.5891
Structures	0.0202	0.1805	0.4156
Equipment and software	0.0138	0.2106	0.5945
Residential	0.0152	0.1935	0.4885
Exports	0.0141	0.1338	0.2969
Goods	0.0173	0.1352	0.3137
Services	0.008	0.0618	0.1614
Imports	0.0058	0.1682	0.4787
Goods	0.0045	0.16	0.4601
Services	0.0094	0.0949	0.2909
Government consumption expenditures and gross investment	0.0042	0.0318	0.0874

Table A.2. AR versus Factor Model: Mean squared forecast errors, relative to the series' variance.

MSFE of the forecast/Variance of the Series	AR			Factor Model, mixed frequency		
Quarter Q+1 ends in, months	*3*	*2*	*1*	*3*	*2*	*1*
Consumption	0.72	0.72	0.72	0.68	0.72	0.74
Services	0.75	0.75	0.75	0.67	1.09	1.09
Non-durables	1.05	1.05	1.05	1.01	0.71	0.75
Durables	1.04	1.04	1.04	0.97	1.01	0.96
Housing Investment	0.46	0.46	0.46	0.43	0.80	0.77
Business Investment	0.66	0.66	0.66	0.34	0.38	0.53
Equipment	0.77	0.77	0.77	0.40	0.39	0.48
Structures	0.70	0.70	0.70	0.65	0.89	0.97
Exports	1.66	1.66	1.66	1.41	0.93	0.84
Imports	1.25	1.25	1.25	0.33	0.30	0.38
GDP	0.91	0.91	0.91	0.56	0.48	0.60