Should macroeconomic forecasters look at daily financial data?*

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1 Introduction

Improving forecasts of macroeconomic indicators such as inflation and economic activity is of focal interest to academics and policy makers, especially in periods of economic turmoil. For instance, the recent economic crisis that started in 2007 has created new challenges to forecasters as they are faced with an empirical failure of their traditional forecasting models and the task to timely revise their forecasts. Faced with these challenges we investigate whether information in the daily financial data can help us better predict quarterly macroeconomic indicators.

While economic theory suggests that financial asset prices have a forward looking behavior and can, therefore, be considered as good predictors for economic conditions, the empirical evidence is mixed and not robust (for example see Stock and Watson (1989, 2002) and Forni, Hallin, Lippi, and Reichlin (2000, 2003)). One issue is that the existing literature ignores that the data involve mixed frequencies: while economic activity and many other macroeconomic variables are typically sampled monthly or quarterly, many financial time series are generally available at a higher frequency (e.g. daily or intradaily). The standard practice in the literature temporally aggregates the financial predictors to the same, low frequency as the dependent macroeconomic variable by computing simple averages. As a result the aggregated processes entail less information, and such a reduction may result in less predictability. This is consistent with the results in Andreou, Ghysels, and Kourtellos (2009) who suggest that the traditional forecasting models, which ignore the different sampling frequencies and simply aggregate the data using equal/flat weights yield inefficient and in some cases inconsistent estimators.

In this paper we employ regression models that involve data sampled at different frequencies, the so called Mi(xed) Da(ta) S(ampling), or MIDAS, regression models. MIDAS was introduced in both forecasting and regression context in a number of recent papers, including including Ghysels, Santa-Clara, and Valkanov (2006), Ghysels, Sinko, and Valkanov (2006), Ghysels and Wright (2007), and Andreou, Ghysels, and Kourtellos (2009), Ghysels and Valkanov (2009), among others. Recent work shows one can improve quarterly macroeconomic forecasts with monthly data using MIDAS regressions; see Clements and Galvao (2008, 2009), Galvao (2006), Marcellino, Schumacher, and Salasco (2008), Ghysels and Valkanov (2009), among others. Moreover, Ghysels and Wright (2007) use daily stock returns and changes in measures of the level and/or slope of the yield curve to predict professional macroeconomic forecasters. Similarly, Hamilton (2008) shows how daily federal funds futures can influence economic activity. The current paper is a substantial effort to show that daily financial data can improve macroeconomic forecasting. There are, however, several new issues that emerge when we try to address the forecasting of macroeconomic series using daily financial data.

In this paper we wish to accomplish three things. First, we forecast key US quarterly indicators of inflation rate and economic growth using a new dataset observed at the mixed frequencies of daily, monthly, and quarterly. Particularly, this dataset updates and extends the Stock and Watson (2008) dataset with daily financial indicators. In doing so we extend the Mi(xed) Da(ta) S(ampling) (MIDAS) regression models to cover new specifications that generalize the simple linear regression, the dynamic linear regression, and the factor models, when one allows for mixed data sampling. Following a large body of recent papers on factor models (e.g. Bai and Ng (2002), Forni, Hallin, Lippi, and Reichlin (2000, 2003, 2005), Stock and Watson (1989, 2002, 2008)), we construct quarterly factors and investigate the improvements in the forecasting ability of the models for two samples. The first sample covers the period 1986-2008 and considers whether 18 of the daily financial series, which are included in the factors at quarterly frequency help to improve the quarterly forecasts of three macroeconomic indicators when they are added to the forecasting model one at a time. The second sample extends the set of financial indicators to 41 financial indicators but it is restricted to the shorter sample of 1999-2008 due to data availability. Second, we examine how we can update our MIDAS models using the real-time data availability especially of daily financial variables which are observed with no measurement error. An important advantage of MIDAS is that it can provide new forecasts as daily data become available while mixing lower frequency data such as factors. For example, suppose we are at the end of September 2008 - with daily data up until the end of September 2008 (and factors kept fixed until 2008Q3). Using MIDAS regression models with leads and lags we can let the daily data absorb all revisions and examine how events like the Lehman bankruptcy affected our forecasts in the subsequent months. Third, we construct two categories of factors: the first is based on quarterly macro factors (using monthly and quarterly macroeconomic data) and the second is based on daily financial factors using a larger cross section of 217 financial series. We estimate daily factors based on both financial returns and volatilities. Finally, we examine whether a MIDAS model, which involves daily financial and quarterly macro factors provides forecasting gains.

Our results provide some interesting findings for forecasting inflation and economic activity for the period 1986-2008. In the case of quarterly IP growth we find that simple univariate MIDAS models for forecasting horizons of one to two quarters ahead, on average outperform the RW as well as traditional Factor model by, 68% and 31%, as well as the simple AR by 69% and 24%, respectively. The maximum gains for forecasting IP growth during this period are obtained by Factor MIDAS models. Similar gains are obtained for the shorter sample period for these MIDAS models. For forecasting CPI inflation the univariate MIDAS model yields forecasting gains for one quarter ahead of about 85%, 53%, and 19% over the RW, AR and FAR, respectively. Interestingly, for longer forecasting horizons of 8 quarters ahead we find that the best MSFE given by the parsimonious univariate MIDAS model yields 28% forecasting gains over the RW and AR and around 50% gains over the traditional Factor models.

Furthermore, we find that on average daily financial predictors improve the forecasts of quarterly inflation and economic activity. For instance, for the 1999-2008 sample we find that some new daily financial predictors optimally filtered via $MIDAS$ models can improve IP growth forecasts for horizons longer than four quarters and provide substantial forecasting gains vis-a-vis the traditional Factor models as well as univariate $MIDAS$ models (and AR and RW models). This evidence is robust across the mean and median MSFE over the 41 daily financial predictors. In the case of CPI inflation we find similar but weaker results (compared to IP growth) for the $MIDAS$ model with daily financial predictors, vis-a-vis the univariate MIDAS and traditional Factor models for $h = 1 - 4$. Moreover, we find that for CPI Inflation the set of best predictors includes the daily indicators of the Aaa bond rate, the crude oil returns, the 10Year Treasury bond spread, Federal funds futures, and A2 P2 F2 minus AA commercial paper spread while the corresponding set of best daily predictors for IP growth also includes the Federal funds futures, as well as crude oil futures and the 1 year and 6 months tbills.

The paper is organized as follows. Section 2 presents the MIDAS models. Section 3 describes the data. Section 4 presents the forecasting results for CPI inflation and IP growth rate. Section 5 deals with daily factors and the last section concludes.

2 MIDAS models

Suppose we want to obtain quarterly or annual forecasts of Y_{t+1} using a predictor $X_{t/m}^{(m)}$ observed m times between $t-1$ and t. For example, suppose we are interested in forecasting the growth rate of industrial production in the next quarter, Y_{t+1}^{Q}, using daily stock returns or interest rates, $X_t^D = X_{t/m}^{(m)}$, where $m = 66$.[1] The conventional approach, in its simplest form, aggregates the data at the quarterly frequency by computing simple averages and estimates a simple linear regression of Y_{t+1}^{Q} on X_t^Q

$$Y_{t+1}^{Q} = \alpha + \beta X_t^Q + u_{t+1} \tag{2.1}$$

where α and β are unknown parameters and u_{t+1} is an error term. In this paper we argue that the implicit assumption in model (2.1), namely that temporal aggregation is based on equal weights of daily data, i.e $X_t^Q = (X_t^D + X_{t-1}^D + ... + X_{t-65}^D)/66$, is restrictive. Instead, we propose a flexible, data-driven aggregation scheme based on a low dimensional high frequency lag polynomial, $W(L^{k_X^D};\theta)$ such that $W(L^{k_X^D};\theta_X^D)X_t^D = \sum_{j=0}^{k_X^D-1} w_j(\theta_X^D)L^j X_{t-j}^D$, where $k_X^D \geq 66$. Following Ghysels, Sinko, and Valkanov (2006b) we employ a two parameter exponential Almon lag polynomial

$$w_j(\theta_1, \theta_2) = \frac{\exp\{\theta_1 j + \theta_2 j^2\}}{\sum_{j=1}^{m} \exp\{\theta_1 j + \theta_2 j^2\}} \tag{2.2}$$

[1]Typically we have about 66 observations of daily data over a quarter since each month has 22 trading days.

with $\theta = (\theta_1, \theta_2)$. This approach allows us to specify a Distributed Lag (DL) model with Mixed Data Sampling (MIDAS) as a linear projection of high frequency data X_t^D onto Y_t^Q

$$DL - MIDAS(1, k_X^D) : Y_{t+1}^Q = \mu + \beta \sum_{j=0}^{k_X^D - 1} w_j(\theta_X^D) L_D^j X_t^D + u_{t+1}. \tag{2.3}$$

The notation $DL - MIDAS(1, k_X^D)$ refers one slope parameter, β, and k_X^D number of high frequency (daily) lags of X_t^D. Note that model (2.3) nests the simple least squares linear regression in (2.1) when $\theta_X^D = (0,0)$ which implies flat-weights and $k_X^D = 66$. We assume that $w_j(\theta) \in (0,1)$ and $\sum_{j=1}^k w_j(\theta) = 1$, that allows the identification of the slope coefficient β in the MIDAS regression model, which we estimate via Nonlinear Least Squares (NLS). In general the conditional mean of the MIDAS regression model (2.3) can be decomposed into an aggregated term based on flat weights and a weighted sum of (higher order) differences of the high frequency variable so that (2.3) becomes

$$DL - MIDAS(k_X^D) : Y_{t+1}^Q = \mu + \frac{\beta}{k} \sum_{j=0}^{k_X^D - 1} X_{t-j}^D + \beta \sum_{j=0}^{k_X^D - 1} \left(w_j(\theta_X^D) - \frac{1}{k} \right) \Delta^{k-j} X_{t-(j-1)}^D + u_{t+1}. \tag{2.4}$$

Equation (2.4) shows that the traditional temporal aggregation approach which imposes flat weights $w_j = 1/k$, such that $X_t^Q = \frac{1}{k} \sum_{j=0}^{k-1} X_{t-j}^D$, yields an omitted variable term in the LS regression model (2.1). We show that the non-linear omitted term, $\sum_{j=0}^{k-1} \left(w_j(\theta_X^D) - \frac{1}{k} \right) \Delta^{k-j} X_{t-(j-1)}^D$, implies that both the AMSE of the LS estimator of β, as well as the one-step-ahead $MSFE^{LS}$ in the simple regression model in (2.1), are relatively larger than the AMSE of the NLS estimator of β and the $MSFE^{NLS}$ in (2.3).

When Y_{t+1}^Q is serially correlated, as is typically the case for time series variables, the simple model in equation (2.1) is extended to a dynamic linear regression or autoregressive distributed lag (ADL) model. Take, for instance, the ADL(1,1)

$$Y_{t+1}^Q = \mu + \alpha Y_t^Q + \beta X_t^Q + u_{t+1}, \tag{2.5}$$

and suppose that Y_t^Q is observed at a higher frequency, like monthly industrial production or inflation, Y_t^M, but nevertheless we wish to forecast quarterly Y_{t+1}^Q because policy makers are interested in quarterly forecasts (e.g. Greenbook forecasts) or because we wish to evaluate our MIDAS macroeconomic forecasts against those based on quarterly factors models benchmarks. In this case we can also allow non-equal weights in the temporal aggregation of Y_t^M to get

$$ADL - MIDAS(1, k_Y^M, 1, k_X^D) : Y_{t+1}^Q = \mu + \alpha \sum_{j=0}^{k_Y^M - 1} w_j(\theta_Y^M) L_M^j Y_t^M + \beta \sum_{j=0}^{k_X^D - 1} w_j(\theta_X^D) L_D^j X_t^D + u_{t+1} \tag{2.6}$$

where k_Y^M and k_X^D refer to the number of high frequency lags of the lag dependent variable, Y_t^M, and regressor, X_t^D, respectively, whilst we keep the low frequency lag structure or slope coefficients, α and β, restricted follow an ADL(1,1) structure.

In general, we define the following MIDAS filtered variables

$$X_t(\theta_X^D) = \sum_{j=0}^{k_X^D-1} w_j(\theta_X^D) L_D^j X_t^D. \tag{2.7}$$

$$Y_t(\theta_Y^M) = \sum_{j=0}^{k_Y^M-1} w_j(\theta_Y^M) L_M^j Y_t^M. \tag{2.8}$$

Then by allowing p_Y and q_X quarterly lags on the MIDAS variables of $Y_t(\theta_Y^M)$ and $X_t(\theta_X^D)$, respectively, we can generalize (2.3) , (2.6) to the following models

$$DL-MIDAS(q_X, k_X^D) : Y_{t+1}^Q = \mu + \sum_{i=0}^{q_X-1} \beta_i L_Q^i X_t(\theta_X^D) + u_{t+1} \tag{2.9}$$

$$ADL-MIDAS(p_Y, k_Y^M, q_X, k_X^D) : Y_{t+1}^Q = \mu + \sum_{i=0}^{p_Y-1} \alpha_i L_Q^i Y_t(\theta_Y^M) + \sum_{l=0}^{q_X-1} \beta_i L_Q^i X_t(\theta_X^D) + u_{t+1}, \tag{2.10}$$

respectively. Note that models (2.9) and (2.10) do not impose any restrictions on the slope coefficients whereas models (2.3) and (2.6) impose the restriction that $\alpha_i = \alpha$ for $i = 0, ..., p_Y$ and $\beta_i = \beta$ for $l = 0, ..., q_X$. They are, nevertheless, considered as parsimonious yet flexible specifications in terms of the lag length of k_X^D and k_Y^M. Under flat weights $\theta_Y^M = \theta_X^D = (0, 0)$ model (2.10) nests the standard $ADL(p_Y, q_X)$ which can be considered as one of the benchmark models for evaluating the predictive ability of daily financial predictors in the spirit of Stock and Watson (2003). We also consider other benchmark models such as the simple $AR(p_Y)$ as well as the univariate MIDAS specifications in:

$$MIDAS(p_Y, k_Y^M) : Y_{t+1}^Q = \mu + \sum_{i=0}^{p_Y-1} \alpha_i L_Q^i Y_t(\theta_Y^M) + u_{t+1}, \tag{2.11}$$

or with the parsimonious version which restricts estimation to a single slope parameter:

$$MIDAS(k_Y^M) : Y_{t+1}^Q = \mu + \alpha \sum_{i=0}^{k_Y^M-1} w_j(\theta_Y^M) L_M^j Y_t^M + u_{t+1}. \tag{2.12}$$

Finally, motivated by the idea of MIDAS one may also apply the exponential Almon lag polynomial (2.2) to the coefficients of the quarterly lags and obtain a more parsimonious specification for (2.10) given by

$$ADL-MIDAS(p_Y^{el},k_Y^M,q_X^{el},k_X^D): Y_{t+1}^Q=\mu+\sum_{i=0}^{p_Y-1} b_i(\widetilde{\theta}_Y)L_Q^i Y_t(\theta_Y^M)+\sum_{i=0}^{q_X-1} b_i(\widetilde{\theta}_X)L_Q^i X_t(\theta_X^D)+u_{t+1}. \tag{2.13}$$

Recently, a large body of recent work has developed factor model techniques that are tailored to exploit a large cross-sectional dimension; see for instance, Bai and Ng (2002) and Bai (2003), Forni, Hallin, Lippi, and Reichlin (2000, 2001, 2003), Stock and Watson (1989, 2002), among many others. These factors are often estimated at quarterly frequency using a large cross-section of monthly and quarterly time-series. Following this literature we investigate whether we can improve factor model forecasts by augmenting such models with high frequency information, especially daily financial data. To do so we augment the aforementioned MIDAS models with factors, F_t, obtained by following dynamic factor model

$$\begin{aligned} X_t &= \Lambda_t F_t + u_t \\ F_t &= \Phi F_{t-1} + \eta_t \\ u_{it} &= a_{it}(L)u_{it-1} + \varepsilon_{it}, \quad i=1,2,...,n \end{aligned} \tag{2.14}$$

where the number of factors is computed using criteria proposed by Bai and Ng (2002).

Augmenting the above MIDAS models with the factors, we obtain a richer family of models that includes monthly frequency lagged dependent variable, quarterly factors, and a daily financial indicator. For instance, equation (2.10) generalizes to

$$\begin{aligned} &FADL-MIDAS(q_F,p_Y,k_Y^M,q_X,k_X^D): \\ &Y_{t+1}^Q=\mu+\sum_{i=0}^{q_F-1}\beta_i L_Q^i F_t^Q+\sum_{i=0}^{p_Y-1}\alpha_i L_Q^i Y_t(\theta_Y^M)+\sum_{i=0}^{q_X-1}\beta_i L_Q^i X_t(\theta_X^D)+u_{t+1}, \end{aligned} \tag{2.15}$$

equation (2.3) yields

$$\begin{aligned} &FDL-MIDAS(q_F,q_X,k_X^D): \\ &Y_{t+1}^Q=\mu+\sum_{i=0}^{q_F-1}\beta_i L_Q^i F_t^Q+\sum_{i=0}^{q_X-1}\gamma_i L_Q^i X_t(\theta_X^D)+u_{t+1}, \end{aligned} \tag{2.16}$$

and equation (2.11) becomes

$$F-MIDAS(p_Y,k_Y^M,q_X): Y_{t+1}^Q=\mu+\sum_{i=0}^{p_Y-1}\alpha_i L_Q^i Y_t(\theta_Y^M)+\sum_{i=0}^{q_F-1}\beta_i L_Q^i F_t^Q+u_{t+1}. \tag{2.17}$$

Note that equation (2.15) simplifies to the traditional factor model with additional regressors when

$\theta_Y^M = \theta_X^D = (0,0)$

$$FADL(q_F, p_Y, q_X) : Y_{t+1}^Q = \mu \sum_{i=0}^{q_F-1} \beta_i L_Q^i F_t^Q + \sum_{i=0}^{p_Y-1} \alpha_i L_Q^i Y_t^Q + \sum_{i=0}^{q_X-1} \gamma_i L_Q^i X_t^Q + u_{t+1} \tag{2.18}$$

as well as the benchmark factor model when the regressor X^Q is not present

$$FAR(q_F, p_Y) : Y_{t+1}^Q = \mu + \sum_{i=0}^{q_F-1} \beta_i L_Q^i F_t^Q + \sum_{i=0}^{p_Y-1} \alpha_i L_Q^i Y_t^Q + u_{t+1}. \tag{2.19}$$

We consider model selection in traditional setting, i.e. with respect to the choice between autoregressive (same frequency) models versus factor models or both combined, but also model selection with respect to the frequency of data (quarterly, monthly or daily). We consider, between zero and four quarterly (low frequency) lags, p_Y, of $Y_t(\theta_Y^M)$ and between one and four quarterly lags, q_X, of $X_t(\theta_X^D)$ and F_t^Q. In terms of the higher frequency lags we consider k_Y^M = 1,2,3,4, and 12 monthly lags of Y_t^M and k_X^D = 66, 132, 198, 264 daily lags of X_t^D. We estimate the models with fixed lags but we also use AIC to select either the number of low frequency or high frequency lags.

Last but not least, we consider the MIDAS models with leads in order to incorporate real-time information available mainly on financial variables. Our objective is to forecast quarterly economic activity and in practice we often have a monthly release of macroeconomic data within the quarter and the equivalent of at least 44 trading days of financial data observed with no measurement error. For instance, Industrial Production and Consumer Price Index data are released on the 15th of the following month. This means that if we stand on the first day of the last month of the quarter and wish to make a forecast for the current quarter we could use up to 1 lead of monthly data and around 44 leads of daily data for financial markets that trade on weekdays.

Consider the Factor ADL model with MIDAS which allows for J_Y^M monthly leads for the lagged dependent variable and daily leads J_X^D for the daily predictor. Then an $FADL - MIDAS$ with leads is given by

$$\begin{aligned} &FADL - MIDAS(q_F, p_Y, , k_Y^M, q_X, k_X^D, J_Y^M, J_X^D) : \\ &Y_{t+1}^Q = \mu + \sum_{i=0}^{q_F-1} \beta_i L_Q^i F_t^Q + \sum_{i=0}^{p_Y-1} \alpha_i L_Q^i Y_{t+J_Y^M}^Q(\theta_Y^M) + \sum_{i=0}^{q_X-1} \beta_i L_Q^i X_{t+J_X^D}^Q(\theta_X^D) + u_{t+1}. \end{aligned} \tag{2.20}$$

When the aggregation weights are flat, $\theta_Y^M = \theta_X^D = (0,0)$, then model (2.20) becomes a simple LS $FADL$ forecasting model with leads.

3 The Data

We use a dataset with mixed frequencies (daily, monthly, and quarterly) that updates and extends the Stock and Watson (2008) dataset using daily financial indicators to forecast quarterly inflation rate and the growth rate of economic activity. We forecast the quarterly inflation rate and the growth rate of economic activity using various measures. For inflation we use monthly Consumer Price Index (CPI) and price indices of Personal Consumption Expenditure (PCEPILFE) and Core inflation (CPILFESL). For economic activity we use monthly Industrial Production (IP), monthly Employees on Nonfarm Payrolls (EMP), quarterly Real Gross Domestic Product (RGDP), and monthly Real Disposable Personal Income (DSPIC96).

Our set of predictors includes 109 quarterly macroeconomic time series for the United States and 41 daily financial indicators. In this paper we focus on two post 1985 samples (the Great Moderation period) because this period appears to mark a structural change in many US macroeconomic variables (Stock and Watson, 2008, van Dijk and Sensier, 2004) and it is also documented that it is relatively difficult to predict key macroeconomic variables vis-a-vis the pre-1985 period and vis-a-vis simple univariate models such as the RW model. The first sample covers the period 02/01/1986 to 31/12/2008 and considers 18 daily financial time, which are identical to those used for the estimation of factor models in Stock and Watson (2002, 2008). The second sample considers an extended set of 41 daily financial predictors for the shorter period of 01/01/1999-31/12/2008 due to data availability. This shorter sample enables us to examine the role of new daily financial predictors in improving macroeconomic forecasts in the last two decades.

Tables A1-A4.2 in the Appendix refer to the variables names, short description and transformations. The data source for the quarterly and monthly series is Haver Analytics, a data warehouse that collects the data series from their individual sources (such as the Federal Reserve Board (FRB) to Chicago Board of Trade (CBOT) and others). The daily financial series were mainly collected from the Global Financial Database (GFD) and FRB unless otherwise stated in Table A3.

Following the methodology of Stock and Watson (2008) we use the series in Tables A1 and A2 to estimate Dynamic Factor models and construct the quarterly factors. The monthly series in Table A2 were aggregated in quarterly values by averaging (in native units) the monthly values over the quarter. As in Stock and Watson (2008) these factor models are based on more monthly subaggregates and excludes higher level aggregates related by identities than the quarterly dataset in Stock and Watson (2002). The series were transformed in order to eliminate trends by first differencing (in many cases after taking logarithms as reported in Tables A1-A4). Table A4 presents estimates of the number of factors, computed using the criteria (ICP) proposed by Bai and Ng (2002). Given that for forecasting purposes the ICP3 would lead to an overparameterized model (with 10 factors) we focus on numbers of factors suggested by the ICP1 and ICP2 criteria. For the larger sample of 1986-2008 the ICP1 suggests three factors (reported in Table A4, Panel A) whereas for the 1999-2008 sample ICP1 yields two factors (found in Table A5, Panel B). For robustness we also revisit our results with the more parsimonious factor models suggested by ICP2.

For the longer sample we estimate our models using the period 1986:Q1-1997:Q1 while forecasts are obtained for the period 1997:Q2-2008:Q4. For the shorter sample the estimation and forecasting windows are given by 1999:Q1-2005Q4 and 2006Q1-2008Q4, respectively. We use the recursive or pseudo out-of-sample forecasting method (see for instance, Stock and Watson, 1993) to evaluate the predictive ability of our models for various forecasting horizons $h = 1, 2, 4, 6, 8$ for the longer sample and $h = 1, 2$ and 4 for the shorter sample. For each model we obtain the absolute MSFE:

$$MSFE(h) = \frac{1}{T_1 - T_2 - h + 1} \sum_{t=T_1}^{T_2-h} (\widehat{Y}_{t+h} - Y_{t+h})^2 \tag{3.21}$$

where the model is estimated for the period $1, ..., T_1$ and the forecasting period is given by $T_1 + h, ..., T_2$.

4 Forecasting Results

4.1 Univariate and Factor models

The discussion of the forecasting results focuses on the models that use both lags and leads since we find that using such information yields in general improved and robust forecast gains compared to just using only lags. The full set of results for all models is available in the Forecasting Results Appendix B.[2] In this section we discuss the univariate and factor models results for forecasting quarterly Consumer Price Index (CPI) inflation and economic activity measured by Industrial Production (IP) growth rate.[3] We first discuss the results for the 1986-2008 sample, that closely relate one of the benchmark forecasting results of Stock and Watson using factor models. Subsequently, we re-evaluate the results for the 1999-2008 sample, given the availability of a larger set of financial predictors.

The forecasting results for the 1986-2008 sample in Table 1(a) report the Root MSFE of the RW model as well as a set of summary statistics of the relative MSFE of univariate MIDAS, given by equations (2.11) and (2.12), and Factor MIDAS models (2.17) vis-a-vis the RW, AR and FAR (2.19) for forecasting horizons $h = 1, 2, 4, 6, 8$. For the univariate models we report the summary statistics of the mean, median, maximum, and minimum of the ratio of the MSFE of RW by the MSFE of all univariate MIDAS specifications (i.e.the relative MSFE of $RW/MIDAS$) given by

[2] This long Appendix is available upon request from the authors.

[3] For conciseness we do not report the results for real GDP, Nonfarm Payroll Employees and CORE inflation.

(2.11) and (2.12) for different choices of quarterly frequency lags, p_Y, and/or monthly frequency lags, k_Y^M, as well as slope parameter restrictions (e.g. exponential almon lag smoothing). We also report the mean, median, maximum, and minimum of relative MSFE of the traditional univariate AR models vis-a-vis the the univariate MIDAS models ($AR/MIDAS$). Similarly, Table 1(a) also reports the summary statistics of the relative MSFE the RW vis-a-vis the Factor MIDAS models ($RW/F-MIDAS$) and the mean, median, maximum, and minimum relative MSFE of the traditional factor (FAR) models, over the corresponding statistics of the Factor MIDAS models ($FAR/F-MIDAS$) . Reported ratios greater than one imply that the MSFEs of MIDAS univariate or factor models improve upon the forecasts of traditional benchmark models such as the RW, AR and FAR models. The discussion below summarizes the main results in Table 1 for CPI inflation and IP growth.

For the 1986-2008 sample the results on CPI inflation show that the simple univariate $MIDAS$ model that optimally weights leads and lags of monthly inflation information to predict quarterly CPI inflation, improves upon the $MSFE$ of the RW (for $h = 1-4$) and the AR (for $h = 1$), but it also improves upon the Factor models. Both the FAR and the $F-MIDAS$ perform poorly for $h = 6$ and 8 vis-a-vis the RW. What is more, neither the traditional Factor models nor the Factor MIDAS models can improve the $MSFE$ of the simple univariate $MIDAS$ model for CPI inflation. This result holds across most of the forecasting horizons $h = 1-6$. More precisely, for $h = 1$ the univariate MIDAS model for CPI inflation yields forecasting gains of about 85%, 53%, and 19% over the RW, AR and FAR, respectively. In fact, for $h = 1$ even the MIDAS model with the poorest (mininum) MSFE improves the forecasts of CPI inflation over the RW, AR and $F-MIDAS$ by 71%, 44%, and 54%, respectively. Interestingly, for $h = 8$ we find that the best MSFE given by the parsimonious univariate MIDAS model in (2.12) with a single slope estimator and a long aggregation horizon of $k_y = 36$ months, yields 28% forecasting gains over the RW and AR and around 50% gains over the Factor models (FAR and $F-MIDAS$). Although for CPI inflation the Factor MIDAS performs well for $h = 1$ vis-a-vis the RW and FAR, it does not outperform the univariate MIDAS, and in addition the $F-MIDAS$ model performs worse than the RW especially for the longer forecasting horizon of $h = 8$.

In Table 1(b) we revisit the above analysis for the shorter sample of 1999-2008. Given the small sample size we focus on $h = 1, 2, 4$. In general, we find that the results for forecasting CPI inflation are similar in the two sample periods. In fact the forecasting gains of the simple univariate $MIDAS$ model based on lags or leads of CPI inflation are even more pronounced for $h = 1$ and they range from 29% (for the worst or minimum MSFE MIDAS model) to just above 100% (for the best MIDAS model) vis-a-vis the RW and the AR benchmarks as well as the Factor MIDAS model. One notable exception is the following: In contrast to the results of 1986-2008 sample, on average the $F-MIDAS$ model does not seem to yield substantial gains over the RW even for $h = 1$, whereas the FAR model provides, on average, 45% gains over the RW for $h = 1$. Note that even the worse or minimum MSFE FAR model exhibits 23% gains over the RW. Nevertheless, the univariate MIDAS model for CPI inflation outperforms the FAR model across all forecasting horizons and summary statistics.

We now turn our discussion to the IP growth forecasting results for the two samples. Tables 1(a) and 1(b) present the results for the 1986-2008 and 1999-2008 samples, respectively. Generally, the results for IP growth for the 1986-2008 sample are qualitatively the same as those for CPI inflation and even stronger. Namely, we find that univariate MIDAS models provide substantial gains over the RW and AR and Factor models for even longer horizons, $h = 1 - 4$. As expected these gains decrease as h increases. For instance, the univariate MIDAS model exhibits forecasting gains for $h = 1$ and $h = 2$ of the range of 55-70% and 19-24% , respectively. Interestingly even the poorest univariate MIDAS model in terms of MSFE is able to outperform the RW and AR. Moreover, the forecasting gains of the univariate $MIDAS$ model over the traditional FAR model for IP growth are even more pronounced. On average the univariate MIDAS MSFE gains are 68% (for $h = 1$) and 31% (for $h = 2$) over the traditional FAR model. It is also worth pointing out that the $F - MIDAS$ model for IP growth also provides MSFE gains vis-a-vis the RW for $h = 1 - 4$ and the FAR for $h = 1 - 2$ and performs better on average than the corresponding models for forecasting CPI inflation. However, although its forecasting performance is on average inferior to that of the univariate $MIDAS$ model, the best $F - MIDAS$ always outperforms the best univariate $MIDAS$. This finding is in contrast to the corresponding result found for CPI inflation as the $F - MIDAS$ always exhibited poor forecasting performance. Turning to Table 1(b) we re-evaluate the forecasting performance of the same models for IP growth for the subsample 1999-2008. We find similar results for the mean, median MSFE gains of univariate MIDAS models for IP growth for $h = 1 - 2$. However, for $h = 4$ the performance of the MIDAS models in terms of the mean and the median MSFE is relatively poor than the corresponding results of the longer sample. Moreover, the range of the MSFEs of the best and worst MIDAS models in the 1999-2008 sample is larger than that of the 1986-2008 sample, suggesting a larger width in the distribution of the MIDAS forecasts. For example, although the maximal gains of the univariate and Factor $MIDAS$ models vis-a-vis the RW for $h = 1 - 2$ increase in 1999-2008 compared to 1986-2008, the poorest MSFEs of MIDAS models can be much worse than the RW. Finally, the $F - MIDAS$ model performs better than the RW for $h = 1 - 2$ and FAR for $h = 1$.

Summing up, in this section we present evidence that suggests that for CPI inflation and IP growth the univariate $MIDAS$ models, on average, can improve the MSFE gains upon all univariate (AR and RW) and Factor models and can therefore be considered as another benchmark model for comparing efficiency gains relative to multivariate $MIDAS$ models (which include daily financial predictors discussed in the next section). However, for IP growth the maximum MSFEs are obtained from Factor models ($F - MIDAS$). Therefore one needs to evaluate whether augmenting the MIDAS model with daily financial variables can improve upon the $MSFE$ of the Factor MIDAS and univariate models for forecasting IP growth and CPI inflation.

4.2 MIDAS models with daily financial predictors

In this section we examine whether the daily information of financial predictors improves the forecasting performance of simple univariate models (RW, AR and MIDAS), Factor models (FAR), discussed in the previous section, as well as traditional Auteregressive Distributed Lag models with financial predictors (e.g. Stock and Watson, 2003) with and without factors (FADL and ADL, respectively). In the first stage we choose to be agnostic and examine the forecasting performance of each financial predictor one at a time (from the list of variables in Tables A3.1 and A3.2 in the Appendix) by estimating various such models, with and without factors, with and without flat weights, all of which are nested in $FADL - MIDAS$ model specification (2.20). The objective of this exercise is twoford. First, we examine whether there are any forecasting gains from using the daily information from 18 financial predictors based on the 1986-2008 sample (listed in Table A3.1) and an extended set of 41 daily financial predictors for the 1999-2008 sample (listed in Table A3.2). We should note that in the case of the 1986-2008 sample the 18 predictors are also included, at quarterly frequency, in the estimation of factors (see also Stock and Watson (2008)) and therefore we can solely attribute any forecasting gains to the daily information. Second, we ask the question whether a data-driven weighting or aggregation scheme of daily predictors improves the forecasting performance vis-a-vis a flat weighting scheme. In the next section we deal with a large cross-section of 217 daily financial predictors and extract the relevant daily factors of returns and volatilities since we find the quarterly factors in the late 1990s sample are robust to the exclusion of the 18 financial predictors in the Stock and Watson (2008) analysis. Consequently we consider these as being quarterly macro factors.

Tables 2(a) and 2(b) report the summary forecasting results for the two samples of 1986-2008 and 1999-2008, respectively. Table 2(a) presents the MSFEs of the $ADL - MIDAS$ and $FADL - MIDAS$ models in equations (2.10) and (2.15) with lags and leads, relative to the RW benchmark as well as the corresponding traditional ADL and $FADL$ models. The summary statistics of the mean, median, maximum and minimum MSFEs are obtain across the 18 daily predictors in Table 2(a) and across the 41 daily predictors in Table 2(b).

For CPI inflation Table 2(a) shows that the $ADL - MIDAS$ models provide substantial MSFE gains (across all statistics) over the RW, ADL, $FADL$ for $h = 1-4$ and over the $FADL-MIDAS$ models during 1986-2008. Table 2(b) shows that we observer similar gains in the mean and median MSFE for the 1999-2008 sample for at least $h = 1, 2$. In contrast, for IP growth Table 2(a) reports that the $FADL-MIDAS$ models provide forecast improvements over the RW, $(F)ADL$ and $ADL-MIDAS$ across all statistics and forecasting horizons $h=1-4$. This result holds for the 1999-2008 period in Table 2(b) where we show that the $(F)ADL-MIDAS$ model yields substantial forecast gains over the RW only for $h=2,4$, whereas for $h=1$ the $ADL-MIDAS$ model is the best forecasting model across all statistics.

In general, for both CPI inflation and IP growth and both samples the $(F)ADL-MIDAS$ specifications provide stronger forecasting gains for early horizons, $h=1,2$, vis-a-vis the (F)ADL, whereas for longer horizons of $h=4,6,8$ they perform as well as the traditional $(F)ADL$ models. For IP growth in the shorter sample of 1999-2008 the relative gains of the $ADL-MIDAS$ model vis-a-vis the traditional ADL model are superior across all statistics compared to the relative relative MSFE of $FADL$ vis-a-vis $FADL-MIDAS$ models.

Last but not least, in 1999-2008 we find that the $(F)ADL-MIDAS$ models for forecasting IP growth for forecasting horizons longer than one year provide substantial forecasting gains over the traditional Factor models (FAR) as well as univariate MIDAS models (and AR and RW models). This evidence is robust across the mean and median MSFE over the 41 daily financial predictors. Similar but weaker results are obtained for the 18 daily financial predictors in the sample period 1986-2008 for IP growth (found in Table 2(a)). Furthermore, for CPI inflation we find similar but weaker results (compared to IP growth for the late 1990s sample) for the $ADL-MIDAS$ model with daily financial predictors over the univariate MIDAS and FAR models for $h=1-4$.

Tables 3(a) and 3(b) identify the best daily financial predictors over the samples of 1986-2008 and 1999-2008, respectively. It is important to mention that we consider other methods of capturing the daily financial information discussed in the paragraph below, it is nevertheless useful to acknowledge the daily financial predictors that yield the maximum MSFE over all models considered in the paper. For example, in Table 3(b) we refer to the relative MSFE of the $(F)ADL-MIDAS$ models vis-a-vis the traditional $(F)ADL$ models and highlight the best three daily predictors for each forecasting horizon, $h=1,2,4$. For forecasting CPI inflation the best daily predictors are the Aaa, the crude oil returns, and the 10Year Treasury bond spread, Federal funds Futures and A2 P2 F2 minus AA commercial paper spread for both $ADL-$ and $(F)ADL-MIDAS$ models. For forecasting IP growth some of the best daily predictors are the Federal Funds futures, the 6 month Treasury bill, the 1 year treasury bond rate and the crude oil futures. Table 3(b) also lists the best daily financial predictors found in the 1986-2008 sample in order to compare these with the three best predictors listed in (1)-(3) during 1999-2008. The interesting result is that crude oil returns, the 10 year treasury bond spread and the 1 year tbill are among the best predictors in both samples and that new daily financial variables appear to yield improved forecast gains.

The above simple analysis provides strong results for $(F)ADL-MIDAS$ suggesting that daily financial variables can improve macroeconomic forecasts over different horizons. Therefore, we consider two alternative but complementary methods for further investigating the above result. First, we employ a model averaging approach to deal with the problem of model uncertainty due to model specification and choice of daily financial predictors. We also compare our results from this approach with various forecast combination methods. Second, we summarize the information of a larger cross-section of daily predictors by constructing daily financial factors and investigating their forecasting performance along with quarterly macro factors.

- Results on Model Averaging and Forecast Combination: To be added -

5 Daily Financial Factors

The above analysis shows that (i) daily financial variables provide substantial gains for forecasting key macroeconomic variables over and above those obtained using quarterly factors and (ii) optimally filtering daily financial information using the data dependent weighting scheme of MIDAS models improves forecasts vis-a-vis the flat weighting scheme of traditional (F)ADL models. A complementary method to evaluate these results is to re-estimate the quarterly factors of Stock and Watson (2008) without the 18 financial variables considered in their analysis and examine whether excluding such information on monthly financial variables worsens the predictions. Such a result would be interpreted as equivalent to the fact that financial variables play a significant role in the extraction of quarterly factors which thereby can lead to prediction gains. This method is similar to Forni, Hallin, Lippi, and Reichlin (2003) applied to forecasting the euro area inflation and real economic activity. However, it should be pointed that applying the Forni et al. method essentially evaluates the role of monthly or quarterly (instead of daily) financial variables in quarterly factors and forecasts, whereas our approach can not only handle this, but also emphasizes that there is useful prediction information in daily financial variables once they are optimally filtered. We find that estimation of the quarterly factors with and without the 18 monthly financial variables (listed in Table A3, Panel A) for the sample 1999-2008 yields the same number of common principal components chosen by ICP1 and ICP2 and also the two factors (chosen by ICP1) are almost equivalent (with sample correlation of 0.996 for the first factor with and without the 18 financial series and sample correlation of 0.973 for the second factor, respetively). Therefore one interpretation of the quarterly factors for the sample 1999-2008 based on the Stock and Watson (2008) panel of variables and method, is that they are dominated by the macro information which we therefore label as being the two quarterly macro factors. Synthesizing this result with the analysis in the previous section on the forecasting gains of daily financial series when included one at a time, we proceed to construct daily financial factors based on a larger cross-section set of 217 daily financial series. Consequently, the first objective is to examine whether a MIDAS forecasting model based on quarterly macro factors and daily financial factors improves macroeconomic forecasts and to compare this approach with the forecast combination and model averaging methods in the previous section. The second objective is to construct common factors based on the daily returns and daily volatilities of financial variables which can be used to evaluate their predictive performance but can also be useful in addressing other interesting questions in the literature.

- To be completed -

6 Conclusion

- To be completed -

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Appendix A

Tables A1-A3 list 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. The transformation codes in Tables A1-A3 are defined below, along with the h-period ahead version of the variable used in the direct forecasting regressions. We let Y_t denote the original (native) untransformed series.

Code	Transformation	$h - \textit{quarter ahead}$ variable
1	$X_t = Y_t$	$X_t^{(h)} = Y_{t+h}$
2	$X_t = \Delta Y_t$	$X_t^{(h)} = Y_{t+h} - Y_t$
3	$X_t = \Delta^2 Y_t$	$X_t^{(h)} = h^{-1} \sum_{j=1}^{h} \Delta Y_{t+h-j} - \Delta Y_t$
4	$X_t = \ln Y_t$	$X_t^{(h)} = \ln Y_{t+h}$
5	$X_t = \Delta \ln Y_t$	$X_t^{(h)} = \ln Y_{t+h} - \ln Y_t$
6	$X_t = \Delta^2 \ln Y_t$	$X_t^{(h)} = h^{-1} \sum_{j=1}^{h} \Delta \ln Y_{t+h-j} - \Delta \ln Y_t$
7	$X_t = 400\Delta \ln Y_t$	$\ln X_t^{(h)} = \frac{400}{h} (\ln Y_{t+h} - \ln Y_t)$

Table 1(a): MSFE Comparisons of MIDAS models with Univariate and Traditional Factor Models

Lags and Leads and Sample 1986-2008

	CPI Inflation					IP growth				
Forecast Horizon	1	2	4	6	8	1	2	4	6	8
RW	1.59	1.27	1.11	0.91	0.72	3.66	3.44	3.05	2.68	2.51
$RW/MIDAS$										
mean	1.85	1.43	1.36	1.11	0.95	4.07	2.15	1.37	1.23	1.15
median	1.84	1.39	1.37	1.13	1.00	4.14	2.18	1.42	1.29	1.21
max	2.06	1.59	1.49	1.15	1.28	4.21	2.20	1.46	1.30	1.23
min	1.71	1.35	1.27	1.02	0.72	3.54	1.94	1.06	0.85	0.78
$AR/MIDAS$										
mean	1.53	1.02	1.06	0.98	0.97	1.69	1.24	1.04	0.98	1.02
median	1.54	0.99	1.06	0.99	1.00	1.71	1.23	1.08	1.03	1.06
max	1.66	1.12	1.15	1.00	1.28	1.67	1.24	1.09	1.02	1.03
min	1.44	0.99	1.01	0.93	0.77	1.55	1.19	0.82	0.69	0.78
$RW/F-MIDAS$										
mean	1.55	1.18	1.06	0.87	0.67	3.56	1.80	1.30	1.10	0.91
median	1.60	1.19	1.04	0.90	0.67	3.15	1.67	1.25	1.15	0.94
max	1.79	1.39	1.49	1.10	0.84	4.50	2.39	1.64	1.36	1.20
min	1.11	0.85	0.55	0.42	0.32	2.23	1.24	1.04	0.75	0.63
$FAR/F-MIDAS$										
mean	1.39	1.03	1.01	0.94	0.86	1.48	1.10	0.99	0.97	1.03
median	1.39	1.04	0.99	0.97	0.93	1.27	0.97	1.00	1.00	1.08
max	1.50	1.12	1.23	1.04	0.79	1.62	1.21	1.06	1.01	1.01
min	1.12	0.83	0.60	0.55	0.56	1.20	1.00	0.95	0.87	0.91

Table 1(b): MSFE Comparisons of MIDAS models with Univariate and Traditional Factor Models

Lags and Leads and Sample 1999-2008						
	CPI Inflation			IP growth		
Forecast Horizon	1	2	4	1	2	4
RW	1.92	1.58	1.33	2.11	2.85	3.04
$RW/MIDAS$						
mean	2.08	1.15	0.92	4.64	1.68	0.80
median	2.26	1.18	0.97	5.46	1.91	0.86
max	2.29	1.43	1.11	5.85	1.91	0.96
min	1.29	0.70	0.38	0.62	0.45	0.23
$AR/MIDAS$						
mean	2.03	1.09	0.93	1.96	1.21	0.85
median	2.22	1.13	0.98	2.34	1.38	0.91
max	2.16	1.28	1.11	2.36	1.35	1.00
min	1.29	0.70	0.40	0.27	0.33	0.26
$RW/F-MIDAS$						
mean	1.18	0.82	0.85	2.08	1.52	0.81
median	0.82	0.76	0.93	2.21	1.80	0.56
max	2.07	1.17	1.01	4.55	2.14	1.48
min	0.64	0.62	0.43	0.99	0.74	0.24
$FAR/F-MIDAS$						
mean	1.45	1.04	0.86	1.25	1.11	0.88
median	1.01	1.04	0.99	1.19	1.01	0.51
max	2.07	1.06	0.75	1.63	0.96	1.00
min	1.23	1.19	0.57	0.94	1.12	0.59

Table 2(a): MSFE Comparisons of MIDAS Models and Traditional Models using Daily Predictors

Lags and Leads and Sample 1986-2008

	CPI Inflation					IP growth				
Forecast Horizon	1	2	4	6	8	1	2	4	6	8
$RW/ADL-MIDAS$										
mean	1.88	1.61	1.51	1.17	0.99	4.30	2.33	1.50	1.31	1.21
median	1.83	1.59	1.51	1.18	1.01	4.27	2.26	1.46	1.34	1.21
max	2.21	2.01	1.74	1.36	1.20	4.80	2.89	1.80	1.57	1.57
min	1.76	1.42	1.26	0.98	0.72	3.94	2.07	0.95	0.72	0.54
$RW/FADL-MIDAS$										
mean	1.82	1.41	1.34	1.01	1.09	4.60	2.51	1.67	1.34	1.19
median	1.78	1.39	1.30	1.06	1.07	4.59	2.37	1.61	1.39	1.20
max	2.31	1.91	1.68	1.45	1.65	5.22	3.13	1.87	1.75	1.87
min	1.67	1.30	1.14	0.87	0.70	3.87	2.17	1.33	0.84	0.63
$ADL/ADL-MIDAS$										
mean	1.52	1.17	1.19	1.04	1.04	1.66	1.21	1.03	1.03	1.01
median	1.50	1.16	1.19	1.05	1.03	1.62	1.21	1.03	1.03	1.02
max	1.76	1.49	1.27	1.18	1.12	1.79	1.30	1.13	1.07	1.08
min	1.45	1.03	1.02	0.98	0.98	1.48	1.07	0.92	0.97	0.94
$FADL/FADL-MIDAS$										
mean	1.55	1.19	1.16	1.07	1.01	1.57	1.18	1.01	1.00	1.00
median	1.53	1.18	1.17	1.05	1.00	1.60	1.20	1.03	1.00	1.00
max	1.66	1.42	1.30	1.29	1.07	1.83	1.31	1.08	1.06	1.08
min	1.45	1.08	1.06	0.92	0.97	1.37	0.98	0.88	0.91	0.91

Table 2(b): MSFE Comparisons of MIDAS Models and Traditional Models using Daily Predictors

Lags and Leads and Sample 1986-2008

	CPI Inflation			IP growth		
Forecast Horizon	1	2	4	1	2	4
$RW/ADL-MIDAS$						
mean	2.22	1.53	1.08	5.26	1.73	2.06
median	2.11	1.28	1.10	4.51	1.55	1.37
max	3.72	4.80	1.54	15.82	4.99	7.45
min	1.58	0.91	0.60	1.55	0.61	0.51
$RW/FADL-MIDAS$						
mean	1.69	1.38	1.14	2.68	1.95	2.73
median	1.69	1.07	1.02	2.83	1.90	1.93
max	2.45	5.53	3.29	3.93	3.86	32.85
min	1.21	0.82	0.74	1.36	0.59	0.73
$ADL/ADL-MIDAS$						
mean	1.86	1.24	1.07	2.59	1.21	1.16
median	1.91	1.21	1.07	2.03	1.21	1.12
max	2.28	1.82	1.37	18.38	2.02	2.36
min	1.27	0.92	0.77	0.92	0.61	0.29
$FADL/FADL-MIDAS$						
mean	1.56	1.11	1.09	1.23	0.98	1.13
median	1.59	1.08	1.02	1.15	1.02	1.07
max	1.91	1.53	2.39	2.19	1.63	1.99
min	0.94	0.95	0.85	0.54	0.61	0.7

Table 3(a): Identifying best predictors (lags and leads models) for the sample 1986-2008

	$ADL/ADL-MIDAS$							$FADL/FADL-MIDAS$					
	Forecast Horizon	1	2	4	6	8		Forecast Horizon	1	2	4	6	8
	CPI Inflation												
(1)	1Yr Tr bond	**1.76**	1.12	1.19	1.05	**1.10**	(1)	Oil prices	**1.66**	1.18	1.14	1.00	0.97
(2)	FX Japan	1.47	**1.49**	**1.27**	1.08	1.03	(2)	FX Japan	1.52	**1.42**	1.17	1.05	0.98
(3)	3mths Tbill	1.47	1.07	**1.27**	1.12	1.07	(3)	FX Canada	1.45	1.15	**1.30**	1.04	0.97
(4)	FX Canada	1.48	1.15	1.18	**1.17**	**1.12**	(4)	10Yrs Tr bond	1.58	1.14	1.08	**1.29**	**1.07**
							(5)	3 month Tbill	1.59	1.13	1.18	1.15	**1.07**
	IP growth												
(1)	FedFunds rate	**1.79**	**1.30**	**1.13**	1.06	1.03	(1)	FX Effective	**1.83**	1.22	1.03	0.91	0.91
(2)	Baa-10Yrs sprd	1.75	**1.30**	1.09	1.04	1.04	(2)	Baa-10Yrs sprd	1.64	**1.31**	1.08	1.05	**1.08**
(3)	Oil Prices	1.71	1.22	1.09	**1.07**	1.02	(3)	1Yr Trbond-FF sprd	1.39	1.21	**1.08**	1.03	1.02
(4)	10Yrs Trbond-FF sprd	1.53	1.18	1.11	1.07	**1.08**	(4)	5Yrs Trbond-FF sprd	1.39	1.21	**1.08**	1.03	1.02
							(5)	FX Japan	1.62	1.23	1.02	**1.06**	1.03

Table 3(b): Identifying best predictors (leads and lags models) for the sample 1999-2008

$ADL/ADL-MIDAS$					$FADL/ADL-MIDAS$				
Forecast Horizon		1	2	4	Forecast Horizon		1	2	4
CPI Inflation									
(1)	Aaa	**2.28**	1.20	1.13	(1)	FedFunds futures1	**1.91**	–	–
(2)	Oil Prices	1.48	**1.82**	1.00	(2)	Oil Prices	1.38	**1.53**	1.21
(3)	10Yrs Tr bond-FF sprd	1.83	1.09	**1.37**	(3)	A2 P2 F2-AA sprd	1.58	1.20	**2.39**
(4)	1Yr Tr bond	2.07	1.41	–	(4)	FX Japan	1.34	1.22	0.89
(5)	FX Japan	1.77	1.14	–	(5)	FX Canada	1.43	1.29	0.85
(6)	3mths Tbill	2.03	1.42	–	(6)	10Yrs Tr bond	1.75	–	–
(7)	FX Canada	1.27	1.19	1.10	(7)	3 month Tbill	1.56	–	–
IP growth									
(1)	FedFunds futures1	**18.38**	1.43	0.29	(1)	1Yr Trbond rate	**2.19**	0.63	1.35
(2)	FedFunds futures3	3.92	**2.02**	0.73	(2)	FX UK returns	1.12	**1.63**	1.64
(3)	6mths Tbill	1.35	0.62	**2.36**	(3)	Oil futures	1.12	1.04	**1.99**
(4)	FedFunds rate	3.10	1.05	1.49	(4)	FX Effective	0.68	1.10	1.05
(5)	Baa-10Yrs sprd	1.50	0.61	0.67	(5)	Baa-10Yrs sprd	1.10	0.90	1.17
(6)	Oil Prices	2.71	1.34	1.33	(6)	1Yr Trbond-FF sprd	1.68	0.61	0.99
(7)	3mths Tbill-FF sprd	2.03	–	–	(7)	5Yrs Trbond-FF sprd	1.68	0.61	0.99
(8)	10Yrs Trbond-FF sprd	2.56	1.46	–	(8)	FX Japan	1.41	1.01	1.02

Appendix

Tables A2-A4 list 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 transformation codes in Tables A2-A4 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_t denotes the original (native) untransformed series.

Table A1:

Code	Transformation	$h-quarter\ ahead$ variable
1	$X_t = Y_t$	$X_t^{(h)} = Y_{t+h}$
2	$X_t = \Delta Y_t$	$X_t^{(h)} = Y_{t+h} - Y_t$
3	$X_t = \Delta^2 Y_t$	$X_t^{(h)} = h^{-1} \sum_{j=1}^{h} \Delta Y_{t+h-j} - \Delta Y_t$
4	$X_t = \ln Y_t$	$X_t^{(h)} = \ln Y_{t+h}$
5	$X_t = \Delta \ln Y_t$	$X_t^{(h)} = \ln Y_{t+h} - \ln Y_t$
6	$X_t = \Delta^2 \ln Y_t$	$X_t^{(h)} = h^{-1} \sum_{j=1}^{h} \Delta \ln Y_{t+h-j} - \Delta \ln Y_t$
7	$X_t = 400\Delta \ln Y_t$	$\ln X_t^{(h)} = \frac{400}{h} (\ln Y_{t+h} - \ln Y_t)$

Table A1: Quarterly Data Appendix

Name - Mnemonic	Description	Start date	End date	
RGDP	Real Gross Domestic Product (SAAR, Bil.Chn.2000$)			
	Description of Quarterly Series used in the Quarterly S&W Factors Model			**Trans. Coc**
Cons-Dur	Real Personal Consumption Expenditures - Durable Goods , Quantity Index (2000=	1959-1	2008-4	5
Cons-NonDur	Real Personal Consumption Expenditures - Nondurable Goods, Quantity Index (200	1959-1	2008-4	5
Cons-Serv	Real Personal Consumption Expenditures - Services, Quantity Index (2000=100) ,	1959-1	2008-4	5
NonResInv-Struct	Real Gross Private Domestic Investment - Nonresidential - Structures, Quantity	1959-1	2008-4	5
NonResInv-Bequip	Real Gross Private Domestic Investment - Nonresidential - Equipment & Software	1959-1	2008-4	5
Res.Inv	Real Gross Private Domestic Investment - Residential, Quantity Index (2000=100	1959-1	2008-4	5
Exports	Real Exports, Quantity Index (2000=100) , SAAR	1959-1	2008-4	5
Imports	Real Imports, Quantity Index (2000=100) , SAAR	1959-1	2008-4	5
Gov Fed	Real Government Consumption Expenditures & Gross Investment - Federal, Quantit	1959-1	2008-4	5
Gov State/Loc	Real Government Consumption Expenditures & Gross Investment - State & Local, Q	1959-1	2008-4	5
Labor Prod	OUTPUT PER HOUR ALL PERSONS: BUSINESS SEC(1982=100,SA)	1959-1	2008-4	5
Real Comp/Hour	REAL COMPENSATION PER HOUR,EMPLOYEES:NONFARM BUSINESS(82=100,SA)	1959-1	2008-4	5
Emp. Hours	HOURS OF ALL PERSONS: NONFARM BUSINESS SEC (1982=100,SA)	1959-1	2008-4	5
Unit Labor Cost	UNIT LABOR COST: NONFARM BUSINESS SEC (1982=100,SA)	1959-1	2008-4	5
PCED-DUR-MOTORVEH	Motor vehicles and parts Price Index	1959-1	2008-4	6
PCED-DUR-HHEQUIP	Furniture and household equipment Price Index	1959-1	2008-4	6
PCED-DUR-OTH	Other Price Index	1959-1	2008-4	6
PCED-NDUR-FOOD	Food Price Index	1959-1	2008-4	6
PCED-NDUR-CLTH	Clothing and shoes Price Index	1959-1	2008-4	6
PCED-NDUR-ENERGY	Gasoline, fuel oil, and other energy goods Price Index	1959-1	2008-4	6
PCED-NDUR-OTH	Other Price Index	1959-1	2008-4	6
PCED-SERV-HOUS	Housing Price Index	1959-1	2008-4	6
PCED-SERV-H0-ELGAS	Electricity and gas Price Index	1959-1	2008-4	6
PCED-SERV-HO-OTH	Other household operation Price Index	1959-1	2008-4	6
PCED-SERV-TRAN	Transportation Price Index	1959-1	2008-4	6
PCED-SERV-MED	Medical care Price Index	1959-1	2008-4	6
PCED-SERV-REC	Recreation Price Index	1959-1	2008-4	6
PCED-SERV-OTH	Other Price Index	1959-1	2008-4	6

PFI-NRES-STR Price Index	Structures	1959-1	2008-4	6
PFI-NRES-EQP	Equipment and software Price Index	1959-1	2008-4	6
PFI-RES	Residential Price Index	1959-1	2008-4	6
PEXP	Exports Price Index	1959-1	2008-4	6
PIMP	Imports Price Index	1959-1	2008-4	6
PGOV-FED	Federal Price Index	1959-1	2008-4	6
PGOV-SL	State and local Price Index	1959-1	2008-4	6

Table A2: Monthly Data Appendix

Name - Mnemonic	Description	Start da	End date	
CPI	CPI-U: All Items (SA, 1982-84=100)	1959-1	2008-12	
IP	IP: Total Index (SA, 2002=100)	1959-1	2008-12	
EMP	Employees: Total Nonfarm (SA, Thous) Payroll	1959-1	2008-12	
	Description of Monthly Series used in the Quarterly S&W Factors Model			**Trans.**
IP: cons dble	INDUSTRIAL PRODUCTION INDEX - DURABLE CONSUMER GOODS	1959-1	2008-12	5
iIP:cons nondble	INDUSTRIAL PRODUCTION INDEX - NONDURABLE CONSUMER GOODS	1959-1	2008-12	5
IP:bus eqpt	INDUSTRIAL PRODUCTION INDEX - BUSINESS EQUIPMENT	1959-1	2008-12	5
IP: dble mats	INDUSTRIAL PRODUCTION INDEX - DURABLE GOODS MATERIALS	1959-1	2008-12	5
IP:nondble mats	INDUSTRIAL PRODUCTION INDEX - NONDURABLE GOODS MATERIALS	1959-1	2008-12	5
IP: mfg	INDUSTRIAL PRODUCTION INDEX - MANUFACTURING (SIC)	1959-1	2008-12	5
IP: fuels	INDUSTRIAL PRODUCTION INDEX - FUELS	1959-1	2008-12	5
NAPM prodn	NAPM PRODUCTION INDEX (PERCENT)	1959-1	2008-12	1
Capacity Util	CAPACITY UTILIZATION - MANUFACTURING (SIC)	1959-1	2008-12	1
Real AHE: const	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - CONSTRUCTION (CES277/PI071)	1959-1	2008-12	5
Real AHE: mfg	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - MFG (CES278/PI071)	1959-1	2008-12	5
Emp: mining	EMPLOYEES, NONFARM - MINING	1959-1	2008-12	5
Emp: const	EMPLOYEES, NONFARM - CONSTRUCTION	1959-1	2008-12	5
Emp: dble gds	EMPLOYEES, NONFARM - DURABLE GOODS	1959-1	2008-12	5
Emp: nondbles	EMPLOYEES, NONFARM - NONDURABLE GOODS	1959-1	2008-12	5
Emp: services	EMPLOYEES, NONFARM - SERVICE-PROVIDING	1959-1	2008-12	5
Emp: TTU	EMPLOYEES, NONFARM - TRADE, TRANSPORT, UTILITIES	1959-1	2008-12	5
Emp: wholesale	EMPLOYEES, NONFARM - WHOLESALE TRADE	1959-1	2008-12	5
Emp: retail	EMPLOYEES, NONFARM - RETAIL TRADE	1959-1	2008-12	5
Emp: FIRE	EMPLOYEES, NONFARM - FINANCIAL ACTIVITIES	1959-1	2008-12	5
Emp: Govt	EMPLOYEES, NONFARM - GOVERNMENT	1959-1	2008-12	5
Help wanted indx	INDEX OF HELP-WANTED ADVERTISING IN NEWSPAPERS (1967=100;SA)	1959-1	2008-12	2
Help wanted/emp	EMPLOYMENT: RATIO; HELP-WANTED ADS:NO. UNEMPLOYED CLF	1959-1	2008-12	2
Emp CPS nonag	CIVILIAN LABOR FORCE: EMPLOYED, NONAGRIC.INDUSTRIES (THOUS.,SA)	1959-1	2008-12	5
U: all	UNEMPLOYMENT RATE: ALL WORKERS, 16 YEARS & OVER (%,SA)	1959-1	2008-12	2
U: mean duration	UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS (SA)	1959-1	2008-12	2
U < 5 wks	UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5 WKS (THOUS.,SA)	1959-1	2008-12	5
U 5-14 wks	UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS (THOUS.,SA)	1959-1	2008-12	5

U 15+ wks	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS + (THOUS.,SA)	1959-1	2008-12	5
U 15-26 wks	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS (THOUS.,SA)	1959-1	2008-12	5
U 27+ wks	UNEMPLOY.BY DURATION: PERSONS UNEMPL.27 WKS + (THOUS,SA)	1959-1	2008-12	5
Avg hrs	AVG WKLY HOURS, PROD WRKRS, NONFARM - GOODS-PRODUCING	1959-1	2008-12	1
Overtime: mfg	AVG WKLY OVERTIME HOURS, PROD WRKRS, NONFARM - MFG	1959-1	2008-12	2
HStarts: NE	HOUSING STARTS:NORTHEAST (THOUS.U.)S.A.	1959-1	2008-12	4
HStarts: MW	HOUSING STARTS:MIDWEST(THOUS.U.)S.A.	1959-1	2008-12	4
HStarts: South	HOUSING STARTS:SOUTH (THOUS.U.)S.A.	1959-1	2008-12	4
HStarts: West	HOUSING STARTS:WEST (THOUS.U.)S.A.	1959-1	2008-12	4
FedFunds	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA)	1959-1	2008-12	2
3 mo T-bill	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)	1959-1	2008-12	2
1 yr T-bond	INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)	1959-1	2008-12	2
10 yr T-bond	INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)	1959-1	2008-12	2
fygm6-fygm3	fygm6-fygm3	1959-1	2008-12	1
fygt1-fygm3	fygt1-fygm3	1959-1	2008-12	1
fygt10-fygm3	fygt10-fygm3	1959-1	2008-12	1
FYAAAC-Fygt10	FYAAAC-Fygt10	1959-1	2008-12	1
FYBAAC-Fygt10	FYBAAC-Fygt10	1959-1	2008-12	1
M1	MONEY STOCK: M1(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL$,SA)	1959-1	2008-12	6
MZM	MZM (SA) FRB St. Louis	1959-1	2008-12	6
M2	MONEY STOCK:M2(M1+O'NITE RPS,EURO$,G/P&B/D MMMFS&SAV&SM TIME DEP(BIL$,	1959-1	2008-12	6
MB	MONETARY BASE, ADJ FOR RESERVE REQUIREMENT CHANGES(MIL$,SA)	1959-1	2008-12	6
Reserves tot	DEPOSITORY INST RESERVES:TOTAL,ADJ FOR RESERVE REQ CHGS(MIL$,SA)	1959-1	2008-12	6
Reserves nonbor	DEPOSITORY INST RESERVES:NONBORROWED,ADJ RES REQ CHGS(MIL$,SA)	1959-1	2008-12	6
BUSLOANS	Commercial and Industrial Loans at All Commercial Banks (FRED) Billions $ (SA)	1959-1	2008-12	6
Cons credit	CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19)	1959-1	2008-12	6
Com: spot price (real)	Real SPOT MARKET PRICE INDEX:BLS & CRB: ALL COMMODITIES(1967=100) (PSCCOM/PCEP	1959-1	2008-12	5
OilPrice (Real)	PPI Crude (Relative to Core PCE) (pw561/PCEPiLFE)	1959-1	2008-12	5
NAPM com price	NAPM COMMODITY PRICES INDEX (PERCENT)	1959-1	2008-12	1
Ex rate: avg	UNITED STATES;EFFECTIVE EXCHANGE RATE(MERM)(INDEX NO.)	1959-1	2008-12	5
Ex rate: Switz	FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.$)	1959-1	2008-12	5
Ex rate: Japan	FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$)	1959-1	2008-12	5
Ex rate: UK	FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)	1959-1	2008-12	5
EX rate: Canada	FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$)	1959-1	2008-12	5
S&P 500	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)	1959-1	2008-12	5
S&P: indust	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS (1941-43=10)	1959-1	2008-12	5
S&P div yield	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)	1959-1	2008-12	2

S&P PE ratio	S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%,NSA)	1959-1	2008-12	2
DJIA	COMMON STOCK PRICES: DOW JONES INDUSTRIAL AVERAGE	1959-1	2008-12	5
Consumer expect	U. OF MICH. INDEX OF CONSUMER EXPECTATIONS(BCD-83)	1959-1	2008-12	2
PMI	PURCHASING MANAGERS' INDEX (SA)	1959-1	2008-12	1
NAPM new ordrs	NAPM NEW ORDERS INDEX (PERCENT)	1959-1	2008-12	1
NAPM vendor del	NAPM VENDOR DELIVERIES INDEX (PERCENT)	1959-1	2008-12	1
NAPM Invent	NAPM INVENTORIES INDEX (PERCENT)	1959-1	2008-12	1
Orders (ConsGoods)	NEW ORDERS (NET) - CONSUMER GOODS & MATERIALS, 1996 DOLLARS (BCI)	1959-1	2008-12	5
Orders (NDCapGoods)	NEW ORDERS, NONDEFENSE CAPITAL GOODS, IN 1996 DOLLARS (BCI)	1959-1	2008-12	5

Table A3: Daily Data Appendix: Panel A

Name - Mnemonic	Description	Source	Start date	End date
FF	Interest rate: Federal Funds (effective) (% per annum)	FRB	02-Jan-86	30-Sep-08
3mths Tbill rate	Interest rate: US treasury bills. Sec mkt, 3-mo (% per annum)	FRB	02-Jan-86	30-Sep-08
1Yr Treasure bond rate	Interest rate: US Treasury Const Maturities, 1-yr (%per annum)	FRB	02-Jan-86	30-Sep-08
10Yrs Treasure bond rate	Interest rate: US Treasury Const Maturities, 10-yrs (%per annum)	FRB	02-Jan-86	30-Sep-08
6mths - FF Spread	6month yield - federal funds rate	FRB	02-Jan-86	30-Sep-08
1Yr - FF Spread	1year yield - federal funds rate	FRB	02-Jan-86	30-Sep-08
10Yrs - FF Spread	10year yield - federal funds rate	FRB	02-Jan-86	30-Sep-08
Aaa-10Year Spread	Aaa-10 Year bond yield	FRB	02-Jan-86	30-Sep-08
Baa-10Year Spread	Baa-10 Year bond yield	FRB	02-Jan-86	30-Sep-08
FX Effective major index	US Effective Exchange rate (Index No), Major	GFD	02-Jan-86	30-Sep-08
FX Swiss	Foreign exchange rate: SWITZERLAND (SWISS FRANC PER U.S.$)	GFD	02-Jan-86	30-Sep-08
FX Japan	Foreign exchange rate: JAPAN (YEN PER U.S.$)	GFD	02-Jan-86	30-Sep-08
FX UK	Foreign exchange rate: UNITED KINGDOM (CENTS PER POUND)	GFD	02-Jan-86	30-Sep-08
FX Canada	Foreign exchange rate: CANADA (CANADIAN $ PER U.S.$)	GFD	02-Jan-86	30-Sep-08
DJIA	Dow Jones Industrial Average Price Index	GFD	02-Jan-86	30-Sep-08
Crude Oil Prices	Crude Oil-WTI Spot Cushing U$/BBL	GFD	02-Jan-86	30-Sep-08
SP500	Standard & Poors 500 Price Index	Datastream	02-Jan-86	30-Sep-08
SPIndustrial	Standard & Poors Industrials Price Index	Datastream	02-Jan-86	30-Sep-08

Table A3 coninued: Daily Data Appendix: Panel B

bkeveny05	Rates of Inflation compensation (or breakeven inflation rates) zero-coupon 5 years	FRB*	04-Jan-99	31-Dec-08
bkeveny10	Rates of Inflation compensation (or breakeven inflation rates) zero-coupon 10 years	FRB*	04-Jan-99	31-Dec-08
bkeven1f4	Rates of Inflation compensation (or breakeven inflation rates): One year forward 4 years	FRB*	04-Jan-99	31-Dec-08
bkeven1f9	Rates of Inflation compensation (or breakeven inflation rates): One year forward 10 years	FRB*	04-Jan-99	31-Dec-08
bkeven5f5	Rates of Inflation compensation (or breakeven inflation rates): Five-to-ten year forward	FRB*	04-Jan-99	31-Dec-08
Aaa bond rate	Moody's Aaa corporate bond yield	FRB	04-Jan-99	31-Dec-08
Baa bond rate	Moody's Baa corporate bond yield	FRB	02-Jan-99	31-Dec-08
6mths Tbill rate	Interest rate: US treasury bills. Sec mkt, 6-mo (% per annum)	FRB	02-Jan-99	31-Dec-08
5Yrs Treasure bond rate	Interest rate: US Treasury Const Maturities, 5-yrs (%per annum)	FRB	04-Jan-99	31-Dec-08
3mths - FF Spread	3month yield - federal funds rate	FRB	04-Jan-99	30-Sep-08
5Yrs - FF Spread	5year yield - federal funds rate	FRB	04-Jan-99	30-Sep-08
A2/P2/F2 - AA	1-Month A2/P2/F2 -AA Nonfinancial Commercial Paper Spread (% per annum)	FRB	04-Jan-99	31-Dec-08
COMEX Gold Prices	COMEX Gold Prices	GFD	04-Jan-99	31-Dec-08
Effective US FX -broad	US Effective Exchange rate (Index No), Broad	GFD	02-Jan-99	31-Dec-08
FX Euro returns	Foreign Exchange Rate: EURO $ PER U.S.$	GFD	02-Jan-99	31-Dec-08
Oil Futures	Crude oil futures	GFD	04-Jan-99	31-Dec-08
Oil Brent	Crude Oil-Brent Cur. Month FOB U$/BBL	GFD	02-Jan-99	31-Dec-08
Lehman Bond Index	Lehman Bond Index	GFD	04-Jan-99	31-Dec-08
Gold Prices	Gold Prices	GFD	04-Jan-99	30-Sep-08
VIX	Volatility of the S&P500 options new methodology	CBOE	04-Jan-99	31-Dec-08
FFutures1	30-Day Fed Funds Futures: 1-Month Settlement (100-daily avg)	CBOT	04-Jan-99	31-Dec-08
FFutures3	30-Day Fed Funds Futures: 3-Month Rolling Contract Settlement (100-daily avg)	CBOT	04-Jan-99	31-Dec-08
SPFutures	S&P 500 Futures Price: 1st Expiring Contract Settlement (Index)	CME	04-Jan-99	31-Dec-08

Notes:
FRB* These data are constructed by Gurkayynak, Sack and Wright (2008), "The TIPS yield curve and inflation compensation", Federal Reserve Board WP

Table A4: Bai and Ng Estimated ICP for various samples

Panel A:

Sample Period:
01/1986 - 09/2008
All Stock and Watson (2008) variables

Sample sizes:
T = 91
N = 108

Nfac	ICP1	ICP2	ICP3
0	-0.0111	-0.0111	-0.0111
1	-0.1806	-0.1682	-0.2100
2	-0.1966	-0.1719	-0.2554
3	-0.2066	-0.1695	-0.2948
4	-0.2015	-0.1520	-0.3191
5	-0.1942	-0.1323	-0.3412
6	-0.1849	-0.1107	-0.3613
7	-0.1692	-0.0826	-0.3749
8	-0.1499	-0.0509	-0.3851
9	-0.1312	-0.0199	-0.3958
10	-0.1123	0.0114	-0.4063

Estimated Number of Factors

ICP1	ICP2	ICP3
3	2	10

Panel B:

Sample Period:
01/1986 - 12/2008
All Stock and Watson (2008) variables

Sample sizes:
T = 40
N = 108

Nfac	ICP1	ICP2	ICP3
0	-0.02532	-0.02532	-0.02532
1	-0.2758	-0.265	-0.2991
2	-0.2863	-0.2647	-0.333
3	-0.2785	-0.2462	-0.3486
4	-0.2753	-0.2322	-0.3688
5	-0.2556	-0.2016	-0.3724
6	-0.2385	-0.1737	-0.3787
7	-0.2237	-0.1481	-0.3872
8	-0.2052	-0.1189	-0.3921
9	-0.1896	-0.09243	-0.3998
10	-0.1619	-0.05393	-0.3955

Estimated Number of Factors

ICP1	ICP2	ICP3
2	1	9

Panel C:

Sample Period:
01/1986 - 12/2008
Excluding 18 Monthly Stock and Watson (200
Financial Series (which are available daily)

Sample sizes:
T = 40
N = 90

Nfac	ICP1	ICP2	ICP3
0	-0.02532	-0.02532	-0.02532
1	-0.2741	-0.2608	-0.3018
2	-0.2862	-0.2596	-0.3416
3	-0.2758	-0.236	-0.3589
4	-0.2632	-0.2101	-0.374
5	-0.2428	-0.1764	-0.3814
6	-0.2268	-0.1472	-0.3931
7	-0.2154	-0.1225	-0.4094
8	-0.1989	-0.09271	-0.4206
9	-0.1792	-0.05971	-0.4286
10	-0.1568	-0.02397	-0.4338

Estimated Number of Factors

ICP1	ICP2	ICP3
2	1	10