Should macroeconomic forecasters use daily financial data and how?*

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First Draft: May 2009
This Draft: February 22, 2010

Abstract

Hundreds of daily financial series contain information about the economy. Can we use all this information for improving and/or updating macroeconomic forecasts? We introduce easy to implement regression-based methods for predicting inflation and real activity that rely on MIDAS regressions either using a combinations of MIDAS regressions involving daily series or using a small set of financial daily factors. Both have the important features that: (1) they allow us to clearly show the incremental value of daily financial series in terms of forecasting, (2) they provide a succinct summary of huge amounts of daily financial data, (3) they allow for real-time updates of forecasting or so called nowcasting.

*The second author benefited from funding by the Federal Reserve Bank of New York through the Resident Scholar Program. We would like to thank Tobias Adrian, Jennie Bai, Jushan Bai, Frank Diebold, Rob Engle, Ana Galvão, Michael Fleming, Serena Ng, Simon Potter, Lucrezia Reichlin, Jim Stock, Mark W. Watson as well as seminar participants at the Banque de France, Banca d'Italia, Board of Governors of the Federal Reserve, Columbia University, Deutsch Bundesbank, Federal Reserve Bank of New York, HEC Lausanne, Queen Mary University, the University of Pennsylvania, the University of Chicago, and the CIRANO/CIREQ Financial Econometrics Conference, MEG Conference, 2009 EC^2 Conference - Aarhus, and the NBER Summer Institute for comments. We also thank Constantinos Kourouyiannis and in particular Michael Sockin for providing excellent research assistance.

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1 Introduction

Theory suggests that the forward looking nature of financial asset prices should contain information about the future states of the economy and therefore should be considered as extremely relevant for macroeconomic forecasting. There are a huge number of financial times series available on a daily basis. However, since macroeconomic data are typically sampled at quarterly or monthly frequency, the standard approach is to match macro data with monthly or quarterly aggregates of financial series to build prediction models. Overall, the empirical evidence in support of forecasting gains due to the use of quarterly or monthly financial series is rather mixed and not robust.[1] To take advantage of the data-rich financial data environment one faces essentially two key challenges: (1) how to handle the mixture of sampling frequencies i.e. matching daily (or weekly or potentially intra-daily) financial data with quarterly (or monthly) macroeconomic series when one wants to predict over relatively long horizons, like one or two years ahead, and (2) how to summarize or extract the relevant information from the vast cross-section of daily financial series. In this paper we address both challenges.

Not using the readily available daily series has two important implications: (1) one looses information through temporal aggregation and (2) one foregoes the possibility of providing real-time daily, weekly or monthly updates of forecasts. Regarding the loss of information through aggregation, there are a few studies that addressed the mismatch of sampling frequencies in the context of macroeconomic forecasting. These studies use state space models, which consist of a system with two types of equations, measurement equations linking observed series to a latent state process, and state equations describing the state process dynamics. The Kalman filter can then be used to predict low frequency macro series, using both past high and low frequency observations. This system of equations requires a lot of parameters, for the measurement equation, the state dynamics and their error processes.[2] Such models can be considered as more complex in terms of specification, estimation and computation of forecasts, compared to the approach proposed in this paper. If we were to use large sets of daily series, this means formulating a large system of equations that describes the dynamics of all the series involved. Instead the approach we propose is regression-based

[1] See for example Stock and Watson (2003) and Forni, Hallin, Lippi, and Reichlin (2003)

[2] See for example, Harvey and Pierse (1984), Harvey (1989a), Bernanke, Gertler, and Watson (1997), Zadrozny (1990), Mariano and Murasawa (2003), Mittnik and Zadrozny (2004), Aruoba, Diebold, and Scotti (2009), Ghysels and Wright (2009), Kuzin, Marcellino, and Schumacher (2009), among others.

and reduced form - notably not requiring to model the dynamics of each and every daily predictor series. In order to deal with data sampled at different frequencies we use the so called MIDAS, meaning Mi(xed) Da(ta) S(ampling), regressions.[3] Such regressions can in fact be viewed as reduced form estimates of the Kalman filter prediction formula - with the reduced form being under-identified vis-à-vis the fully specified state space model since the regression involves only a small set of parameters.[4] Another approach to study the effects of information loss of imposing the traditional temporal aggregation has been addressed analytically in a regression setup by Andreou, Ghysels, and Kourtellos (2010), who show that the estimated slope coefficient of a regression model that impose the standard flat aggregation approach (and ignore the fact that processes are generated from a mixed data environment) can yield asymptotically inefficient and in some cases inconsistent estimates. Consequently, this can be translated to forecast losses.

A number of recent papers have documented the advantages of using such MIDAS regressions in terms of improving quarterly macro forecasts with monthly data, or improving quarterly and monthly macroeconomic predictions with a small set (typically one or a few) of daily financial series.[5] These studies neither address the question how to handle the information in large cross-sections of high frequency financial data, nor the potential usefulness of such series for real-time forecast updating. Several recent papers also documented the gains of real-time forecast updating, sometimes also nowcasting when it applies to current quarter assessments.[6] These studies used again the state space setup - and therefore face the same computational complexities pointed out earlier. Here too, MIDAS regressions provide a relatively easy to implement alternative. The simplicity of the approach allows us to produce nowcasts with potentially a large set of real-time data feeds.

[3] MIDAS regressions were suggested in recent work by Ghysels, Santa-Clara, and Valkanov (2004), Ghysels, Santa-Clara, and Valkanov (2006) and Andreou, Ghysels, and Kourtellos (2010). The original work on MIDAS focused on volatility predictions, see also Alper, Fendoglu, and Saltoglu (2008), Chen and Ghysels (2009), Engle, Ghysels, and Sohn (2008), Forsberg and Ghysels (2006), Ghysels, Santa-Clara, and Valkanov (2005), León, Nave, and Rubio (2007), among others.

[4] Bai, Ghysels, and Wright (2009) discuss the relationship between state space models and the Kalman filter.

[5] See e.g. Kuzin, Marcellino, and Schumacher (2009), Armesto, Hernandez-Murillo, Owyang, and Piger (2009),Clements and Galvão (2009), Clements and Galvão (2008), Galvão (2006), Schumacher and Breitung (2008), Tay (2007), for the use of monthly data to improve quarterly forecasts and improving quarterly and monthly macroeconomic predictions with one daily financial series, see e.g.Ghysels and Wright (2009), Hamilton (2006), Tay (2006).

[6] Nowcasting is studied at length by Doz, Giannone, and Reichlin (2008), Doz, Giannone, and Reichlin (2006), Stock and Watson (2007), Angelini, Camba-Mendez, Giannone, Rünstler, and Reichlin (2008), Giannone, Reichlin, and Small (2008), Moench, Ng, and Potter (2009), among others.

To deal with the potential large cross-section of daily series we suggest two approaches: (1) forecast combinations or model averaging of forecasting regressions with a large set of daily financial series, and (2) extract a small set of daily financial factors from a large cross-sectionof around one thousand financial time series which cover five main classes of assets - equities, foreign exchange, corporate risk, commodities prices and fixed income. These factors are then used in our forecasting models as in (1) above.

Our results provide some interesting findings for forecasting US economic activity and inflation for the period 1999-2008. We find that forecast combinations of MIDAS models with daily predictors as well as daily factors provide substantial forecasting gains relative to the benchmark forecasting models considered in the literature. The daily factors appear to have useful information for forecasting economic activity beyond the information included in the quarterly factors for US real GDP growth, for both 1 and 4 quarters ahead. More importantly we find that MIDAS models can efficiently incorporate real-time information using daily leads within the quarter and thereby provide accurate forecasts which are robust to alternative methods of forecast combinations. For core inflation we find that the leading information contained in daily predictors and daily financial factors play a complementary role in forecasting one quarter and one year ahead, respectively, PCEcore inflation.

The paper is organized as follows. In section 2 and 3 we describe the MIDAS Regression Models and discuss our data, quarterly and daily factors. In section 6 we present our results and section 7 concludes.

2 MIDAS Regression Models

Suppose we want quarterly forecasts of Y^Q_{t+1} of say inflation or GDP growth. Denote by X^Q_t a quarterly aggregate of a financial predictor series (the aggregation scheme being used is, say, averaging). One conventional approach, in its simplest form, is to use a so called $ADL(p^Q_Y, q^Q_X)$ regression model:

$$Y^Q_{t+1} = \mu + \sum_{j=0}^{p^Q_Y-1} \alpha_{j+1} Y^Q_{t-j} + \sum_{j=0}^{q^Q_X-1} \beta_{j+1} X^Q_{t-j} + u_{t+1} \qquad (2.1)$$

which involves p_Y^Q lags of Y_t^Q and q_X^Q lags of X_t^Q. This regression is fairly parsimonious as it only requires $p_Y^Q + q_X^Q + 1$ parameters to be estimated. Assume now that we would like to use the daily observations of X. Denote $X_{N_D-j,t}^D$, the daily predictor in the j^{th} day counting backwards in quarter t. Hence, the last day of quarter t corresponds with $j = 0$ and is therefore $X_{N_D-j,t}^D$. A naive approach would be to estimate - in the case of $p_Y^Q = q_X^Q = 1$ the regression:

$$Y_{t+1}^Q = \mu + \alpha_1 Y_t^Q + \sum_{j=0}^{N_D-1} \beta_{1,j} X_{N_D-j,t}^D + u_{t+1} \tag{2.2}$$

where N_D denotes the daily lags or the number of trading days per quarter. This is unappealing approach because of parameter proliferation: when $N_D = 66$, we have to estimate 68 slope coefficients. A MIDAS regression approach consists of hyper-parameterizing the polynomial lag structure in the above equation, yielding what we will call a $ADL - MIDAS(p_Y^Q, q_X^D)$ regression:

$$Y_{t+1}^Q = \mu + \sum_{j=0}^{p_Y^Q-1} \alpha_{j+1} Y_{t-j}^Q + \beta \sum_{j=0}^{q_X^D-1} \sum_{i=0}^{N_D-1} w_{i+j*N_D}(\theta^D) X_{N_D-i,t-j}^D + u_{t+1} \tag{2.3}$$

where, to simplify notation, we will always take lags in blocks of quarterly sets of daily data, hence the notation. Following Ghysels, Santa-Clara, and Valkanov (2006) and Ghysels, Sinko, and Valkanov (2006), we use a two parameter exponential Almon lag polynomial

$$w_j(\theta) \equiv w_j(\theta_1, \theta_2) = \frac{\exp\{\theta_1 j + \theta_2 j^2\}}{\sum_{j=1}^{m} \exp\{\theta_1 j + \theta_2 j^2\}} \tag{2.4}$$

with $\theta = (\theta_1, \theta_2)$. This approach allows us to obtain a linear projection of high frequency data X_t^D onto Y_t^Q with a small set of parameters. Note that this yields a general and flexible function of data-driven weights.[7]

At this point several issues emerge. Some issues are theoretical in nature. For example, to what extend is this tightly parameterized formulation in (2.3) able to approximate the unconstrained (albeit practically infeasible) projection in equation (2.2)? There is also the question the regression in (2.3) relates to the more traditional approach involving the Kalman

[7] Other parameterizations of the MIDAS weights have been used. One restriction implied by (2.4) is the fact that the weights are always positive. We find this restriction reasonable for many applications. The great advantage is the parsimony of the exponential Almon scheme. For further discussion, see Ghysels, Sinko, and Valkanov (2006).

filter would be more suitable. We do not deal directly with these types of questions here, as they have been addressed notably in Bai, Ghysels, and Wright (2009) and Kuzin, Marcellino, and Schumacher (2009). However, some short answers to these questions are as follows. First, it turns out that a MIDAS regression can be viewed as a reduced form representation of the linear projection that emerges from a state space model approach - by reduced form we mean that the MIDAS regression does not require the specification of a full state space system of equations. For illustrative purposes, consider a simple dynamic single factor model:

$$F_{i,t} = \rho F_{(i-l),t} + \eta_{i,t} \qquad \forall t = 1, \ldots, T, \qquad i = 2, \ldots, N_D \tag{2.5}$$

and $F_{1,t} = \rho F_{N_D,t-1} + \eta_{1,t}$. Moreover, let $\eta_{.,t}$ be i.i.d. Gaussian with mean zero and variance σ_η^2. Suppose now the daily data $x_{i,t}^D$ relates to the factors as follows:

$$x_{i,t}^D = \gamma F_{i,t} + u_{i,t} \qquad i \neq N_D \tag{2.6}$$

with $u_{.,t}$ i.i.d. Gaussian with mean zero and variance σ_u^2. Finally, at the end of each quarter, we have:

$$x_{N_D,t}^D = \gamma F_{N_D,t} + u_{N_D,t} \qquad\qquad y_t^Q = F_{N_D,t} + v_{N_D,t} \tag{2.7}$$

with $v_{.,t}$ i.i.d. Gaussian with mean zero and variance σ_v^2. This highly stylized state space model with mixed sampling and minimal parametric specification (involving five parameters collected in $\theta^S \equiv (\rho, \gamma, \sigma_\eta^2, \sigma_u^2, \sigma_v^2)$). Bai, Ghysels, and Wright (2009) show that the steady state Kalman filter corresponds to the following $ADL - MIDAS(\infty, \infty)$:

$$E_t[Y_{t+1}^Q] = \sum_{j=0}^{\infty} \alpha_{j+1}(\theta^S) Y_{t-j}^Q + \beta \sum_{j=0}^{\infty} \sum_{i=1}^{N_D} w_{i+j*n_D}(\theta^S) X_{i,t-j}^D \tag{2.8}$$

where $E_t[]$ is linear projection using past quarterly and daily data combined. The weights have a structure very similar to the MIDAS regression appearing in (2.3) and a related one discussed below in equation (2.10). It is important to note that the Kalman filter requires to specify a complete system of equations, which we kept to an absolute minimum representation in the above motivating example. Nevertheless, we counted five parameters driving the weights in equation (2.8) compared to two for the Exponential Almon weighting scheme of the MIDAS regression. In some cases the MIDAS regression is an exact representation of the Kalman filter, in other cases it involves approximation errors that are typically small.[8]

[8]Bai, Ghysels, and Wright (2009) discusses both the cases where the mapping is exact and the

The Kalman filter, while clearly optimal as far as linear projections goes, has two main disadvantages (1) it is more prone to specification errors as a full system of equations for Y, X, and latent factors is required and (2) as already noted it requires a lot more parameters to achieve the same goal. This is particularly relevant for the cases we cover in this paper. Namely handling a combination of quarterly and daily data leads to large state space system equations prone to mis-specification. MIDAS regressions, in comparison, are frugal in terms of parameters and achieve the same goal. More parameters and a system of equations also means that estimation is more numerically involved - something that is not so appealing when dealing with large data sets - as we will. In the remainder of this section we expand on the main theme addressed so far. Namely, we will present several MIDAS regression specifications that cover more general cases.

2.1 Temporal aggregation, multiplicative MIDAS regressions and the Kalman filter

It is worth pointing out that there is a more subtle relationship between the ADL regression appearing in equation (2.1) and the ADL-MIDAS regression in equation (2.3). Note that the ADL regression involves temporally aggregated series, based for example on equal weights of daily data, i.e.

$$X_t^Q \equiv (X_{1,t}^D + X_{2,t}^D + ... + X_{N_D,t}^D)/N_D$$

If we take the case of N_D days of past daily data in an ADL regression, then implicitly through the aggregation we have picked the weighting scheme β_1/N_D for the daily data $X_{\cdot,t}^D$. We will sometimes refer this scheme as a *flat* aggregation scheme. While these weights have been used in the traditional temporal aggregation world, it may not be optimal for time series data which most often exhibit a downward memory decay structure (Ghysels, Santa-Clara, and Valkanov (2006)), or for the purpose of forecasting as more recent data may be more informative and thereby get more weight. In general though, the ADL-MIDAS regression lets the data decide what those weights should be and the exponential Almon function allows for a flexible and general shape of weights.

The comparison with temporal aggregation prompts us to consider two MIDAS regression

approximation errors in cases where the MIDAS does not coincide with the Kalman filter.

models that allow for quarterly lags. First, define the following filtered parameter-driven *quarterly* variable

$$X_t^Q(\theta_X^D) \equiv \sum_{i=0}^{N^D-1} w_i(\theta_X^D) X_{N_D-i,t}^D, \tag{2.9}$$

Then, we can define the $ADL - MIDAS - M(p_Y^Q, p_X^Q)$ model, where $-M$ refers to the fact that the model involves a multiplicative weighting scheme, namely:

$$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_X^Q-1} \beta_k X_{t-k}^Q(\theta_X^D) + u_{t+1} \tag{2.10}$$

and $ADL - MIDAS - M(p_Y^Q[r], p_X^Q[r])$ model:

$$Y_{t+1}^Q = \mu + \alpha \sum_{k=0}^{p_Y^Q-1} w_k(\theta_Y^Q) Y_{t-k}^Q + \beta \sum_{k=0}^{p_X^Q-1} w_k(\theta_X^Q) X_{t-k}^Q(\theta_X^D) + u_{t+1}. \tag{2.11}$$

Both equations (2.10) and (2.11) apply MIDAS aggregation to the daily data of one quarter but they differ in the way they treat the quarterly lags. More precisely, while equation (2.10) does not restrict the coefficients of the quarterly lags, equation (2.11) restricts the coefficients of the quarterly lags - hence the notation $p_X^Q[r]$ - by hyper-parameterizing these coefficients using a multiplicative MIDAS polynomial.[9] Both specifications nest the equally weighted aggregation scheme.

It is worth revisiting the Kalman filter again, more precisely equation (2.8). Bai, Ghysels, and Wright (2009) show that the weighting scheme in equations (2.10) and (2.11) corresponds to the structure of a steady state Kalman filter linear projection with mixed sampling frequencies. Namely,

$$E_t[Y_{t+1}^Q] = \sum_{j=0}^{\infty} \alpha_{j+1}(\theta^S) Y_{t-j}^Q + \beta \sum_{j=0}^{\infty} \sum_{i=1}^{N_D} w_k(\theta^S) X_{t-k}^Q(\theta^S) \tag{2.12}$$

with $X_{t-k}^Q(\theta^S)$ similar to $X_t^Q(\theta_X^D)$ appearing in equation (2.9). The downside of the MIDAS specification in equations (2.10) and (2.11) is that it is less parsimonious than the single

[9] The multiplicative MIDAS scheme was originally suggested for purpose of dealing with intra-daily seasonality in high frequency data, see Chen and Ghysels (2009).

weighting scheme in equation (2.3). Yet, it typically involves less parameters than the multiplicative scheme emerging from the Kalman filter appearing in driven by θ^S. Note also that equation (2.11) is more parsimonious than equation (2.10), and at the same time also more restrictive.

2.2 MIDAS Regression Models with Factors

We develop two strategies to address the use of high frequency financial data for forecasting key macroeconomic variables. One involves the use of MIDAS regressions with a single high frequency regressor - using a cross-section of daily financial series- and then combine the forecasts they generate. The second involves extracting factors from two large cross-sections that involve quarterly data and daily financial data. The latter approach involves extracting financial factors that span many series within the equities, foreign exchange, fixed income and commodity prices. These daily financial factors can be used for many other applications beyond the present forecasting analysis.

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), Bai (2003), Forni, Hallin, Lippi, and Reichlin (2000), Forni, Hallin, Lippi, and Reichlin (2005), Stock and Watson (1989), Stock and Watson (2003), among many others. These factors are usually estimated at quarterly frequency using a large cross-section of time-series. Following this literature we investigate first whether we can improve factor model forecasts by augmenting such models with high frequency information, especially daily financial data. Subsequently, we will construct *daily* factors, using the large cross-section of financial series.

We augment the aforementioned MIDAS models with factors, F_t, obtained by following factor model

$$\begin{aligned} X_t &= \Lambda_t F_t + u_t \qquad (2.13) \\ F_t &= \Phi F_{t-1} + \eta_t \\ u_{it} &= a_{it}(L) u_{it-1} + \varepsilon_{it}, \quad i = 1, 2, ..., n. \end{aligned}$$

The data used to implement the factor representation will be described in the next section. Suffice it here to say that we use series similar to those used by Stock and Watson (2008a). The number of factors are chosen based on the information criteria proposed by Bai and Ng

(2002).

We augment the MIDAS regression models from the previous subsection by adding quarterly factors. For instance, equation (2.3) generalizes to the $FADL-MIDAS(p_Y^Q, p_F^Q, k_X^D)$ model

$$\begin{aligned} Y_{t+1}^Q &= \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_F^Q-1} \beta_k F_{t-k}^Q \\ &\quad + \gamma \sum_{j=0}^{p_X^D-1} \sum_{i=0}^{N_D-1} w_{i+j*N^D}(\theta_X^D) X_{N_D-i,t-j}^D + u_{t+1} \end{aligned} \tag{2.14}$$

Note that we can also formulate a $FADL-MIDAS-M(p_Y^Q, p_F^Q, p_X^Q)$ model, which involves the multiplicative MIDAS weighting scheme, hence generalizing equation (2.10). Notice also that equation (2.15) simplifies to the traditional factor model with additional regressors when the MIDAS features are turned off - i.e. say a flat aggregation scheme is used. When the lagged dependent variable is excluded then we have a projection on daily data, combined with aggregate factors. This brings us to the following benchmark models of $FADL(p_Y^Q, p_F^Q, p_X^Q)$

$$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_F^Q-1} \beta_k F_{t-k}^Q + \sum_{k=0}^{p_X^Q-1} \gamma_k X_{t-k}^Q + u_{t+1} \tag{2.15}$$

and $FAR(p_Y^Q, p_X^Q)$ when the regressor X^Q is not present

$$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_F^Q-1} \beta_k F_{t-k}^Q + u_{t+1} \tag{2.16}$$

Finally, we consider model selection in the traditional setting, i.e. with respect to the choice between autoregressive (same frequency) models versus factor models or both combined. 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 daily lags we consider the following multiples of the number of trading days, and $p_X^D = 1, 2, 3, 4$. We estimate the models with fixed lags but we also use AIC to select the number of quarterly and/or daily lags.

2.3 Nowcasting and Leads

Giannone, Reichlin, and Small (2008), among others, have formalized the process of updating the nowcast and forecasts as new releases of data become available. This process can be mimicked via MIDAS regression models with *leads*. Say we are one or two months into quarter $t+1$. Namely, 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. 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 and around 44 leads of daily data for financial markets that trade on weekdays.

Consider the Factor ADL model with MIDAS in equation (2.15), which allows for J_X^D daily leads for the daily predictor, expressed in multiples of months, $J_X^D = 1, 2, ..., J$. Then we can specify the $FADL - MIDAS(p_Y^Q, p_F^Q, p_X^D, J_X^D)$ model

$$\begin{aligned} Y_{t+1}^Q &= \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_F^Q-1} \beta_k F_{t-k}^Q + \gamma[\sum_{i=0}^{J_X^D-1} w_i(\theta_X^D) X_{J_X^D-i,t+1}^D \\ &+ \sum_{j=0}^{p_X^D-1} \sum_{i=0}^{N_D-1} w_{i+j*N^D}(\theta_X^D) X_{N_D-i,t-j}^D] + u_{t+1}, \end{aligned} \quad (2.17)$$

3 Data

We forecast the US quarterly growth rate of economic activity and inflation rate using various measures. We are interested in quarterly forecasts for three reasons: First, one of the key macroeconomic measures for economic activity that academics and policy makers forecast is real Gross Domestic Product (GDP) which is observed at quarterly frequency. Second, policy makers report quarterly forecasts such as, for instance, the Fed's Greenbook forecasts. Third, one of the popular approaches in forecasting these key measures is based on quarterly factor models (e.g. Forni, Hallin, Lippi, and Reichlin (2005), Stock and Watson (2007), and Stock and Watson (2008a)), which is mainly driven from the quarterly data availability of most macro variables.

For economic activity we use Real Gross Domestic Product (GDP) and Industrial Production (IP). For inflation we use Consumer Price Index (CPI), Personal Consumption Expenditure Price Index (PCECTPI) and for Core inflation we use both the CPI and PCE Price indices which exclude food and energy (CPILFESL and PCEPILFE, respectively). For conciseness, here we focus on reporting one economic activity measure, namely real GDP, and two core inflation measures, PCEcore and CPIcore, given that these are the relatively more important series from the US monetary policy perspective. The remaining detailed results and tables are available from the authors upon request.

We study a recent sample period of US data 1/1/1999-31/12/2008 for at least three reasons: First, this period provides a new set of daily financial predictors relative to most of the existing literature on forecasting, including new series such as corporate risk spreads (e.g. the A2P2F2 minus AA nonfinancial commercial paper spread, the eurodollar spreads), term structure variables (e.g. breakeven inflation rates), equity measures (such as the implied volatility of S&P500 index option (VIX), the Nasdaq100 stock market returns index). These predictors are not only related to economic models which explain the forward looking behavior of financial variables for the macro state of the economy (e.g. see, for instance, the comprehensive review in Stock and Watson (2003) but they have been recently monitored by policy makers and practitioners even on a daily basis to forecast inflation and economic activity. Such an example is the break-even inflation rates during the Fed's Federal Open Market Committee (FOMC) meetings and the VIX often coined as the stock market fear-index. Second, for this period the daily data availability allows us to study the role of a large cross-section of daily financial predictors by extracting a small number of daily factors to examine whether these improve macro forecasts in the last two decades over other methods used in the existing literature. Third, we note that this recent period belongs to the post 1985 Great moderation era which is marked as a structural break in many US macroeconomic variables (Stock and Watson (2003), Bai and Ng (2005), Van Dijk and Sensier (2004)) and has been documented that it is more difficult to predict such key macroeconomic variables (D'Agostino, Surico, and Giannone (2009), Rossi and Sekhposyan (2010)) vis-à-vis simple univariate models such as the Random Walk (RW) and Atkeson-Ohanian (AO) models (Atkeson and Ohanian (2001), Stock and Watson (2008b)) (for economic growth and inflation, respectively) and vis-à-vis the pre-1985 period and using inflation survey data (Ang, Bekaert, and Wei (2007)). Hence we take the challenge of predicting inflation and economic growth in a period that many models and methods did not provide substantial forecasting gains over simple models.

We use three databases of two sampling frequencies of macroeconomic and financial indicators. The first is a quarterly dataset from 1999:Q1-2008:Q4 ($T = 40$) of 69 quarterly series of real output and income, capacity utilization, employment and hours, price indices, money, etc., described in detail in the Appendix, Table A2. We use this dataset to extract the quarterly factors. Our quarterly dataset updates that of Stock and Watson (2008b) but excludes variables observed at the daily frequency which we include in our second database which consists of daily series.[10]

Our daily database covers a large cross-section of 988 daily series from 1/1/1999-31/12/2008 ($T = 1777$) for four categories of financial assets which we use to extract a small set of daily financial factors. The four categories of daily financial assets are: (i) the Commodities class includes 241 variables such as US individual commodity prices, commodity indices and futures; (ii) the Corporate Risk category includes 210 variables such as yields such as bonds for various maturities, LIBOR, Certificate of Deposits, Eurodollars, Commercial Paper, default spreads using matched maturities, quality spreads, and other short term spreads such as TED; (iii) the Equities class comprises 219 variables of the major international stock market returns indices and Fama-French factors and portfolio returns as well as US stock market volume of indices and option volatilities of market indices; (iv) the Foreign Exchange Rates class includes 70 variables of the trading partners in the broad index as well as international currency rates of major indices and effective exchange rate indices; (v) the Government Securities include 248 variables of government treasury bonds rates and yields, term spreads, TIPS yields, break-even inflation. These data are described in detail in the online Appendix of the paper.

We create a third daily database which is a subset of the aforementioned large-cross section and involves only 90 daily predictors from the above five categories of financial assets. These 90 daily predictors are proposed in the literature as good predictors of economic growth and inflation. Table A1 in the Appendix presents the details of these predictors (variables names, short description, transformations and data source). Describing briefly these daily predictors we use categorize them into five classes and use: (1) Forty Commodity variables which include Commodity indices, prices and futures (suggested, for instance, in Edelstein

[10]The excluded variables from the quarterly factor analysis are foreign exchange rates of Swiss Franc, Japanese Yen, UK Sterling pound, Canadian Dollar all vis-à-vis the US dollar, the average effective exchange rate, the S&P500 and S&P Industrials stock market indices, the Dow Jones Industrial Average, the Federal Funds rate, the 3 month T-bill, the 1 year Treasury bond rate, the 10 year Treasury bond rate, the corporate bond spreads of Moody's AAA and BBB minus the 10 year government bond rate and the term spreads of 3 month treasury bill, 1 year and 10 year treasury bond rates all vis-à-vis the 3 month treasury bill rate.

(2009)); (2) Sixteen Corporate risk series (following e.g. Bernanke (1983), Bernanke (1990), Stock and Watson (1989), Friedman and Kuttner (1992)); (3) Ten Equity series which include major US stock market indices and the S&P500 Implied Volatility (VIX) (some of which were used in Mitchell and Burns (1938), Harvey (1989b), Fischer and Merton (1984), and Barro (1990)); (4) Seven Foreign Exchanges which include the individual foreign exchange rates of major US trading partners and two effective exchange rates (following e.g. Gordon (1982), Gordon (1998)), Engel and West (2005) and more recently Chen, Rogoff, and Rossi (2010)); (5) Sixteen Government securities which include the federal funds rate, government treasury bills of securities ranging from 3 months to 10 years, the corresponding interest rate spreads (following the evidence, for instance, from Sims (1980), Bernanke and Blinder (1992), Laurent (1988), Laurent (1989), Harvey (1989b), Harvey (1988), Stock and Watson (1989), Estrella and Hardouvelis (1991), Fama (1990), Mishkin (1990b), Mishkin (1990a), Hamilton and Kim (2002), Ang, Piazzesi, and Wei (2006)) and inflation compensation series (of different maturities and forward contracts) (e.g. Gurkaynak, Sack, and Wright (2010)). Last but not least, we consider the daily Aruoba, Diebold and Scotti (ADS) Business Conditions Index, Aruoba, Diebold, and Scotti (2009), which can also be considered as a daily factor based on a small cross-section of US macroeconomic variables of mixed frequency, that complements our daily factors extracted from the larger cross-section of 988 variables mentioned above. Given that this database involves a smaller set of $N = 90$ variables we have ($T = 2251$) which is due to the fact that we have less missing observations when balancing this short cross-section (compared to the larger one of 988 series).

The data sources for the quarterly and daily series are the FRB and 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 Global Financial Database (GFD) and FRB, unless otherwise stated. In a nutshell, using these three datasets we investigate the predictive ability of: (1) quarterly factors; (2) daily factors; (3) 90 daily predictors by examining both their individual predictive ability using a large model space as described in 2, as well as their forecasting ability using various forecast combinations methods discussed in section 5.

4 Daily and Quarterly Factors

Following the methodology of Stock and Watson (2002a), Stock and Watson (2008a) we estimate Dynamic Factor models in (2.13) to construct the factors. In all cases the series were transformed in order to eliminate trends by first differencing (following the transformation code reported in Tables A1 and A2. There are alternative approaches of choosing the number of factors. One approach is to use the information criteria (ICP) proposed by Bai and Ng (2002). In the case of quarterly factors ICP criteria suggest the choice of the first two factors for the period 1999:Q1-2008:Q8. Interestingly, although our quarterly database excludes 20 financial variables from the Stock and Watson database, namely the variables which are available at daily frequency, our first two factors correlate almost perfectly with those of Stock and Watson (with correlation coefficients equal to 0.99 and 0.98 for factors 1 and 2, respectively). Hence the excluded aggregated daily series do not seem to play an important role for extracting the first two factors for the period 1999:Q1-2008:Q4. These first two quarterly factors explain 36% ad 12%, respectively, of the total variation of the panel of quarterly variables. The first quarterly factor correlates highly with Industrial Production and Purchasing Manager's index whereas the second quarterly factor correlates highly with Employment and NAPM inventories index. These results are consistent with Stock and Watson (2008a) that use a longer time-series sample as well as Ludvigson and Ng (2007) and Ludvigson and Ng (2009) that use a different panel of US data.

We now turn to extract daily factors using the Dynamic Factor model from our large cross-section of 988 variables over the same sample period. If we use either of the three ICP criteria in Bai and Ng (2002) we find that they always suggest 10 factors. Table 1, Panel A, shows the standardized eigenvalues for 10 daily factors extracted using the cross-section of 988 predictors as well the factors extracted from the 5 categories of financial assets described above: Commodities (COMM), Corporate risk (CORP), Equities (EQUIT), Foreign Exchange (FX) and Government Securities (GOV). On the basis of the eigenvalue results one may argue that overall the first three factors explain a relatively higher percentage of the cross sectional variation, whereas in contrast the ICP criteria suggest that all 10 factors can be chosen. Instead our objective is to examine the role of these factors in a conditional forecasting framework (as opposed to the unconditional approach of the eigenvalue or ICP criteria). Hence we evaluate each of the 10 daily factor separately by considering one at a time in a forecasting equation as well as jointly using different methods of combining the forecasts from daily factors in order to examine if they help predict inflation and the growth rate of economic activity. [11] Table 1, Panel B, also shows the percentage that each of the five classes of assets loads to each daily factor measured by the cumulative sum of square loadings of the variables in each of the five categories of assets. Using this information we attach a label to each daily factor. For instance, the first daily factor $F^D_{ALL,1}$ is dominated by Government Securities and Commodities, $F^D_{ALL,2}$ can be characterized by Equities, $F^D_{ALL,3}$ by Corporate risk and Government securities and so on. Figures 1 - 3 present the time series plots of the first three daily financial factors using ALL 988 predictors. Figures 4, 5, 6, and 7 present the first daily factor using predictors only from the block of Commodities, Corporate Risk, Equities, and Government, respectively. The first daily factor, $F^D_{ALL,1}$,in Figure 1, is characterized by volatility clustering and with recent high volatility period. The temporal dynamics of this factor are inherited from those of the Government securities and Commodities block of assets. In fact both $F^D_{GOV,1}$ in Figure 7 and $F^D_{COMM,1}$ in Figure 4 exhibit the same temporal dynamics as $F^D_{ALL,1}$. The second daily factor presented in Figure 1 exhibits a recent period of clustered large negative returns. Although this factor highly correlates with the Equities block in Figure 6, one observes that it is only the negative returns that are inherited from $F^D_{EQUIT,1}$ to $F^D_{ALL,2}$. In contrast, $F^D_{EQUIT,1}$ has a recent period of both positive and negative returns. Moving now to the third daily factor we observe that, in contrast to the previous ones, $F^D_{ALL,3}$ exhibits a cyclical behavior and a large cluster of negative returns in the recent period which resembles that of $F^D_{ALL,2}$. Both the cyclical behavior and the downward trend in the recent period of $F^D_{ALL,3}$ in Figure 3 are due to the first factor from the Corporate risk class of assets, $F^D_{CORP,1}$, in Figure 5 whereas the volatility of $F^D_{ALL,3}$, is due to $F^D_{GOV,1}$ in Figure 7. Finally, it is worth noting that our daily financial factors are of independent interest and can be applied in many other areas of financial modeling. Moreover, they complement the analysis of quarterly real/macro factors and quarterly financial factors presented in Ludvigson and Ng (2007) and Ludvigson and Ng (2009) to study the risk-return tradeoff and and bond risk premia.

5 Forecast Appraisals and Combinations

In our forecasting analysis the estimation and prediction windows are given by 1999:Q1-2005Q4 and 2006Q1-2008Q4, respectively. Using a recursive estimation method we provide pseudo out-of-sample forecasts (see for instance, Stock and Watson (2002b) and Stock and

[11] Due to the small time sample we do not consider more than one daily factor in a forecasting equation.

Watson (2003)) to evaluate the predictive ability of our models for various forecasting horizons $h = 1, 2, 4$. For each model we obtain the root MSFE:

$$RMSFE_{i,t} = \sqrt{\frac{1}{t - T_0 + 1} \sum_{\tau=T_0}^{t} (y^h_{\tau+h} - \widehat{y}^h_{i,\tau+h|\tau})^2}. \tag{5.1}$$

where $t = T_1, \ldots, T_2$. T_0 is the point at which the first individual pseudo out-of sample forecast is computed. Note that $T_0 = 2006 : Q1$, $T_1 = 2006 : Q1 + h$, and $T_2 = 2008 : Q4 - h$.[12]

There is a large and growing literature that suggests that forecast combinations can provide more accurate forecasts by using evidence from all the models considered rather than relying on a specific model. Areas of applications include output growth (Stock and Watson (2004)), inflation (Stock and Watson (2008b)), exchange rates (Wright (2008)), and stock returns (Avramov (2002)). Timmermann (2006) provides an excellent survey of forecast combination methods. One justification for using forecast combinations methods is the fact that in many cases we view models as approximations because of the model uncertainty that forecasters face due to the the different set of predictors, the various lag structures, and generally the different modeling approaches. Furthermore, forecast combinations can deal with model instability and structural breaks under certain conditions. For example Stock and Watson (2004) find that forecast combination methods and especially simple strategies such as equally weighting schemes (Mean) can produce more stable forecasts than individual forecasts. In contrast, Aiolfi and Timmermann (2006) show that combination strategies based on some pre-sorting into groups can lead to better overall forecasting performance than simpler ones in an environment with model instability. Although there is a consensus that forecast combinations improve forecast accuracy there is no consensus concerning how to form the forecast weights.

Given M approximating models and associated forecasts, combination forecasts are (time-varying) weighted averages of the individual forecasts,

$$\widehat{f}_{M,t+h|h} = \sum_{i=1}^{M} \widehat{\omega}_{i,t} \widehat{y}_{i,t+h|t}$$

where the weights $\widehat{\omega}_{i,t}$ on the i^{th} forecast in period t depends on the historical performance

[12] Due to sample limitations we do not use the rolling forecasting method.

of the individual forecast.

In this paper we consider mainly three families of forecast combination methods: (i) Simple combination forecasts, (ii) Discounted MSFE forecasts, and (iii) Information criteria based forecasts. Simple combination forecasts include the Mean, the Trimmed Mean (with 5% symmetric trimming), and the Median. According to Timmermann (2006)) while equal weighting methods such as the Mean are simple to compute and perform well, they can also be optimal under certain conditions. Nevertheless, equal weighting methods ignore the historical performance of the individual forecasts in the panel. To account for the historical performance of each individual forecast we use the Discounted MSFE method employed by Stock and Watson (2004) and Stock and Watson (2008b)). This method computes the combination forecast as a weighted average of the individual forecasts, where the weights are inversely proportional to the discounted MSFE (DMSFE) or the square of the discounted MSFE (2DMSFE), using a discount factors $\delta = 0.9$ in order to attach greater weight to the recent forecast accuracy of the individual models.

$$\begin{aligned}\widehat{\omega}_{i,t} &= \frac{\left(\lambda_{i,t}^{-1}\right)^{\kappa}}{\sum_{j=1}^{n}(\lambda_{j,t}^{-1})^{\kappa}} \\ \lambda_{i,t} &= \sum_{\tau=T_0}^{t-h} \delta^{t-h-\tau}(y_{\tau+h}^{h} - \widehat{y}_{i,\tau+h|\tau}^{h})^2,\end{aligned}$$

where $\delta = 0.90$ and $\kappa = 1, 2$. Although we focus on $\delta = 0.9$, we also considered discount factors of $\delta = 1$ and 0.95 but the results remained qualitatively the same.[13] All the results are available from the authors upon request.

For robustness, we also explore three related methods, Recently Best, Best, and Rank based forecast combinations. Recently Best forecast (RBest) is the forecast with the lowest cumulative MFSE over the past 4 quarters (see Stock and Watson (2004)). Best is a time invariant method of forecast combination that places all the weight to the model with the lowest cumulative MFSE over all available out-of sample forecasts. Rank based forecasts computes the combination forecasts as a weighted average of the individual forecasts, where the weights are inversely proportional to the models rank.

The third family of forecast combinations computes the combination forecast as a weighted

[13]Note that the case of no discounting $\delta = 1$ corresponds to the Bates and Granger (1969) optimal weighting scheme when the individual forecasts are uncorrelated.

average of the individual forecasts, where the weights are based on the using in-sample model fit computed by three alternative information criteria: Mallows, Bayesian information criterion (BIC), and Akaike information criterion (AIC). Forecast combination based on the Mallows Model Averaging (MMA) method chooses weights by minimizing the Mallows criterion, which is an approximately unbiased estimator of the MSE and MSFE. MMA was studied by Hansen (2007) in the context of regression and proposed by Hansen (2008) as a forecast combination method. Hansen showed that MMA forecasts are asymptotically optimal (at least in the case of *i.i.d.* regressors and errors), have low MSFE, and exhibit much lower maximum regret than other feasible forecasting methods. More precisely, MMA chooses optimal weights by minimizing the penalized sum of squared residuals

$$\sum_{t=1}^{T}(y_{t+h} - \widehat{f}_{M,t+h}(\omega))^2 + 2s^2 \sum_{m=1}^{M} \omega_m k_m \tag{5.2}$$

such as $\sum_{j=1}^{M} \omega_j = 1$ and $0 \leq \omega_j \leq 1$ where s^2 is an estimate of the variance of the error of the largest fitted model and k_m is the number of parameters of each model.

A popular alternative is based on Bayesian Model Averaging (BMA) weights, which can be approximated by smoothed BIC (SBIC) weights under diffused priors. The success of BMA has been demonstrated by Avramov (2002), Stock and Watson (2006), and Wright (2008). The weights take the following form,

$$\widehat{\omega}_{i,t} = \frac{\exp(-BIC_{i,t+h|t})}{\sum_{j=1}^{n} \exp\left(BIC_{j,t+h|t}\right)} \tag{5.3}$$

where $BIC_{i,t+h|t}$ is the BIC of the i^{th} model based on its h-period performance up to time t. We also consider a related proposal by Burnham and Anderson (2002) who replace the SBIC weights with smoothed AIC weights (SAIC) that use the AIC criterion that places a weaker penalty to larger models.

6 Empirical results

In a first subsection we cover forecasting of economic activity, followed by a subsection dealing with inflation forecasts. The evaluation of forecasts appears in subsection 6.3

6.1 Economic Activity

In this section we discuss the results for forecasting growth of economic activity measured by the US real GDP growth. Table 2, Panel A, presents relative RMSFEs forecast combinations of the benchmark models namely the simple AR models, and quarterly FAR models vis-à-vis that the RW (along with the latter's RMSFE reported in the first row of the Table). Similarly in Panels B and C of Table 2 we report the relative RMSFEs vis-à-vis the RW obtained from the combinations of the 90 predictors and of the 10 daily factors, respectively, using two families of models. These are the traditional ADL and FADL models as well as the corresponding ADL-MIDAS and FADL-MIDAS models with no leads ($J_X = 0$) and with leads ($J_X = 2$). For conciseness we report the results from three alternative forecast combination models, namely the Mean, 2DMSFE and MMA, which imply different approaches of weighting forecasts/models, as discussed in the previous section 5. The robustness analysis examines the rest of the forecast combination methods discussed in 5 and reports the results in Table 8.

The results presented in Table 2 for real GDP growth forecast combinations over the sample period 1999-2008 can be summarized as follows: First we find that combinations of traditional quarterly factor models, FAR, that take into account uncertainty with respect to the dynamics of these quarterly factors as well as the lagged dependent variable, provide $73-79\%$ RMSFEs gains vis-à-vis the RW benchmark as well as simple AR combinations for one quarter ahead forecasts (h=1) only. In general, we find that including the quarterly factors in FADL and FADL-MIDAS models (reported in Panels B and C) improve the RMSFE compared to the corresponding ADL, ADL-MIDAS and FAR models using all three combination method and mostly one quarter ahead forecasts for GDP growth.

Second, the information of the 90 daily predictors (presented in Panel B) turns out to be useful for forecasting GDP growth in either traditional models like FADL or FADL-MIDAS models (with or without leads) since it improves the RMSFE vis-à-vis the RW, AR and FAR. This result holds for both h=1 and 4 using any of the three combinations method. Hence the information from the predictors per se (whether aggregated with flat or data-driven weights) improves forecasting performance relative to all the benchmark models.

Third, the RMSFE of FADL-MIDAS models without leads ($J_X = 0$) is lower than that of FADL for all three combination methods at h=1. This implies that using daily data with a data-driven aggregation scheme improves forecasting performance compared to quarterly data (which imply a flat weighting scheme for the daily information). This evidence extends to h=4 for the 2DMSFE method which provides further evidence for the fact that relevant discounting of models with their MSFE may provide relatively larger gains compared to other combination methods.

Fourth, the highest forecasting gains are obtained from forecast combinations based on the daily leading information of the 90 predictors. In fact strong results are obtained for the forecasting performance of both ADL-MIDAS and FADL-MIDAS models with leads for both forecasting horizons, h=1,4 and for all three combination methods. We find that MIDAS models with leads provide 24% to 64% gains over the RW benchmark. In addition, for h=4 the FADL-MIDAS models with leads provide relative gains of upto 50% compared to the same models with no leads, when using any of the three combinations method. A similar qualitative result is also obtained from the combinations of the 10 daily factors extracted from the cross-section of 988 assets reported in Panel C. Interestingly, the combinations of these 10 daily factors extracted from this large cross-section improve upon the MIDAS models with leads which use only 90 predictors, for both h=1,4, with and without quarterly factors, and for all combination methods.[14] Interestingly, ADL- or FADL-MIDAS models with no leads that use these 10 daily factors provide similar RMSFEs with those of the 90 predictors in Panel B. Hence, it is the leading information in either the 10 daily factors or the 90 daily predictors that actually substantially improves our forecasting performance of GDP growth for both h=1 and especially 4.

Our empirical results provide supportive empirical evidence of the argument that asset prices are forward looking and contain useful information for future output growth relative to the mixed results found, for instance, in Stock and Watson (2003) and Forni, Hallin, Lippi, and Reichlin (2003). Our analysis provides complementary methodological and empirical findings relative to the existing literature, namely: (F)ADL-MIDAS models with leads, exploiting the daily information in individual predictors and daily financial factors. We find that forecast combinations of the leading information from the 90 daily financial predictors and in particular, that of the novel daily financial factors provide substantial forecasting gains, measured by the RMSFE.

We now turn to look deeper into our cross-section and try to identify if there is a particular class of assets that provides the highest forecasting gains. These results are presented in Table 5. For a given combination method, say the 2DMSFE we compare the relative RSMFEs from

[14] The exception is h=4 for 2DMSFE.

all assets vis-à-vis those of the 5 blocks of assets. We do this for the small database of the 90 daily predictors in Panel A and in Panel B we report the corresponding results for the daily factors as well as those extracted from each block of the large cross-section. Table 2 reports two classes of models: The first class involves all the models in our model space namely the traditional (F)-ADL, the (F)-ADL-MIDAS models with no leads and with leads. The second class is a subset of these which comprises the quarterly factor models, FADL and FADL-MIDAS with and without leads. Our objective here is to identify the blocks of assets that yield the relatively larger gains for forecasting GDP growth using, for instance, the MIDAS model with leads. We obtain three interesting results: (i) Combinations of (F)ADL-MIDAS models with leads at h=4 present the highest forecasting gains from either the 90 daily predictors or the 10 daily factors. The driving forces for these gains are the predictors in the following classes of assets: Corporate risk, Equities and FX. This result holds whether we choose to focus on the individual daily predictors in these three classes or the daily factors in each of these blocks. (ii) In fact, forecast combination of daily factors especially from the equities and foreign exchange blocks for the (F)ADL-MIDAS models with leads improves those the corresponding RMSFE from individual predictors in this block by around 45% and 40%, respectively. The gains are even higher when comparing the factors or predictors from these two classes of assets vis-à-vis the traditional (F)ADL models. (iii) Whilst the equities and FX daily factors extracted from the large cross-section of 219 and 70 equity and FX series, respectively, improve the RMSFE from the 10 Equity and 7 FX series in the set of the 90 selected predictors, this is not the case for Corporate Risk. It appears that the latter provides the impressive gain of 12% vis-à-vis the RW for h=4 using (F)ADL-MIDAS models. All the above gains improve when we use both quarterly and daily factors in the context of FADL-MIDAS models. It is also worth noting that among the best predictors for real GDP growth are the Canadian\$/US\$; the A2P2F2 minus AA Fin Commercial paper spreads and the Merrill Lynch A minus 10year Treasury Bond spread; the S&P500 returns, the ADS business conditions index, as well as the seventh and third daily financial factors, $F^D_{ALL,7}$ an $F^D_{ALL,3}$. Last but not least, for h=1 the same classes of assets provide MSFE gains which are nonetheless as strong those of h=4. Note that similar qualitative results are obtained for the blocks of assets using other combination criteria (such as the Mean and MMA).

6.2 Core Inflation

In this section we discuss the results for forecasting inflation that excludes food and energy measured by Personal Consumption Expenditure Price Index (PCEcore) and Consumer Price Index (CPIcore) inflation over the sample period 1999-2008. We first discuss the results of PCEcore inflation given that this is the preferred measure of core inflation by the Federal Reserve of the United States. Since February 2000, the Federal Reserve Boards semiannual monetary policy reports to Congress have described the Boards outlook for inflation in terms of the PCE. Prior to that, the inflation outlook was presented in terms of the CPI. [15]

Table 3, Panel A, presents the RMSFEs of the two benchmark models, the Unobserved Components Stochastic Volatility (UCSV) (Stock and Watson (2007)) and AO (Atkeson and Ohanian (2001)) models. In recent studies these are found as the relevant benchmarks for forecasting US inflation (e.g. Stock and Watson (2008b)). During our sample period the AO and UCSV models provide the same RMSFE for h=4 whereas the UCSV model provides the lowest RMSFE for PCEcore inflation for h=1. Hence we use this as the benchmark model to obtain the relative RMSFEs for the rest of the models reported in Panels A-C of Table 3. In addition, in Panel A we find that for h=4 forecast combinations of the traditional FAR models, based on just the 2DMSFE method, improves upon the UCSV by 77%. In contrast, the other two combinations methods (Mean and MMA) yield relative RMSFE of FAR models very close to one for both h=1 and 4. In fact, we find that combinations of simple AR(p) models using all three methods can yield RMSFEs from 77% (Mean) to 85% (2DMSFE and MMA) relative to the UCSV, at h=4.

Moving to the results in Panels B and C of Table 3 we report the relative RMSFEs vis-à-vis the UCSV from the combinations of the 90 daily predictors and 10 daily factors, in each of these two panels, respectively. We find the following interesting results:

First, the information of the 90 daily predictors and 10 daily factors (presented in Panels

[15] In explaining its preference for the PCE, the Board stated: The chain-type price index for PCE draws extensively on data from the consumer price index but, while not entirely free of measurement problems, has several advantages relative to the CPI. The PCE chain-type index is constructed from a formula that reflects the changing composition of spending and thereby avoids some of the upward bias associated with the fixed-weight nature of the CPI. In addition, the weights are based on a more comprehensive measure of expenditures. Finally, historical data used in the PCE price index can be revised to account for newly available information and for improvements in measurement techniques, including those that affect source data from the CPI; the result is a more consistent series over time. Monetary Policy Report to the Congress, Federal Reserve Board of Governors, Feb. 17, 2000.

B and C, respectively) turns out to be useful for forecasting PCEcore inflation, in either traditional models like (F)ADL or (F)ADL-MIDAS models (with or without leads) when using 2DMSFE combinations. In particular, the 2DMSFE shows RMSFE improvements vis-à-vis the UCSV (or AO) model, ranging from 37% and 32% in traditional FADL with combinations of daily predictors and factors, respectively, for h=4. In fact the 2DMSFE shows that the information from the daily predictors or daily factors, with flat or data-driven weights, improves forecasting performance relative to all the benchmark models (UCSV, AO, AR and FAR). However the evidence in favor of using data-driven weights in the MIDAS models with no leads, vis-à-vis the flat weighting scheme of traditional ADL type models, for PCEcore is weak and mixed and depends upon the method of combination.

Second, we find that in general, and unlike the real GDP growth results discussed in the previous section, including quarterly factors does not always improve forecasts of PCEcore inflation for either forecasting horizon using the Mean and MMA combinations methods. In addition, we find that for PCEcore forecasts, the 2DMSFE combinations method provides the highest relative gains compared to the MMA and Mean methods, across both the 90 predictors and 10 daily factors and across all classes of models presented in Table 3. More importantly, the largest forecasting gains are in general obtained from the combinations of MIDAS models with daily leads and in particular the ADL-MIDAS ($J_X = 2$) models across all h and across all combinations methods. For instance, we find that for h=1 and 4 the 2DMSFE combinations of ADL-MIDAS ($J_X = 2$) models yield relative RMSFEs of 53% and 32% vis-à-vis the UCSV and around 50% relative gains from the corresponding models with no leads, namely the ADL-MIDAS ($J_X = 0$). These gains also apply to models with daily factors as well as the other two combination methods (MMA and Mean), but with smaller relative gains.

Our third finding addresses the question as to which of the two approaches yields relatively more gains, namely whether to combine the leading information from the 90 daily predictors or from the 10 daily factors. Our results show that for PCEcore inflation the role of daily predictors and factors is complementary, since for h=1 daily factors perform better whereas for h=4 it is daily predictors that deliver the forecast gains. For example, using daily factors for h=1 and daily predictors for h=4 in ADL-MIDAS models with leads, we obtain relative forecasting gains of upto 48% and 23%, respectively, vis-à-vis the UCSV benchmark, using, for instance, the 2DMSFE combination method. It is also worth emphasizing that for h=4 combinations of the 90 daily predictors yield forecast gains of upto 45% over the corresponding daily factors, using ADL-MIDAS ($J_X = 2$) models. These results also hold if we use the other two combination methods (the Mean and MMA), albeit weaker compared to the 2DMSFE. In addition, we find that for forecasting PCEcore inflation the quarterly factor in MIDAS models with daily leads, namely FADL-MIDAS ($J_X = 2$), perform consistently worse that then corresponding models with no quarterly factors (ADL-MIDAS ($J_X = 2$)) across all h and forecast combination methods. One explanation for this result is that the literature finds that quarterly factors have less predictive ability in the post Great Moderation period while another explanation is that in these models quarterly factors are kept stale since they only take into account the daily leads information.

We now turn to Table 6 in order to obtain a deeper understanding as to the classes of assets that provide the highest forecasting gains. For coherency with the GDP growth rate results discussed in the previous section, we compare the results for the 2DMSFE from all assets vis-à-vis those of the 5 categories of assets. As mentioned above models with leads yield the lower RMSFE relative to all models with no leads, namely the (F)-ADL and (F)-ADL-MIDAS ($J_X = 0$). Focusing on these (F)-ADL-MIDAS ($J_X = 2$) models and comparing the results for all assets or all factors in Panels A and B, for h=4, we observe that they yield relative RMSFE gains of around 25% and 45%, for the daily predictors and factors, respectively, vis-à-vis the UCSV. Using the 2DMSFE and all (F)ADL-MIDAS models ($J_X = 2$) we find that for h=4 the forecast combinations of the 90 daily predictors with leads are superior to those of the daily factors for PCEcore inflation by 45%. These RMSFE gains are driven from the combinations of the following blocks of assets: the 7 daily FX series, the 16 Government securities and the 16 corporate risk series, found in Table A1. Similar results are obtained when considering a subset of these models, namely the ADL-MIDAS models ($J_X = 2$), for these three blocks. In contrast, the gains are weaker when we impose the quarterly factors in the MIDAS models with leads, as shown by the last set of models in Panel A. Among the best predictors for PCEcore inflation are the Canadian$/US$ and Sterling Pound$/US$, the Federal Funds rate, the 1 Year LIBOR rate, the 6 months treasury bill spread and 6 months Eurodollar spread both with respect to the Federal Funds rate, whereas the best factors are $F^D_{ALL,3}$ an $F^D_{ALL,7}$. Note that the third daily factor, $F^D_{ALL,3}$ and the Canadian$/US$ turn out to be the best predictors for both GDP growth and PCEcore over our sample period. In terms of robustness we also mention that these blocks of assets are also identified as being the barometer of forecast gains even when using the simple Mean forecast combination method for PCEcore as reported in Table 9.

In addition to the above results we find in Panel B of Table 6 that the daily factors extracted from the same blocks of larger cross-section of assets provide the largest gains for PCEcore inflation in (F)ADL-MIDAS models with leads. These refer to forecast combinations of daily factors from each of the following classes of assets: the Corporate risk, Government securities and FX. It is especially interesting to note that the daily Corporate risk factors yield relative RMSFEs of 10% vis-à-vis the UCSV and 27% vis-à-vis the combination of the corresponding 16 daily corporate risk predictors. Stronger forecasting gains from the daily factors of the Corporate risk as well as the Government securities assets can be obtained if one compares the FADL-MIDAS models with leads with the corresponding daily predictors from those classes.

In order to further evaluate our forecasting results for core inflation we also examine the results for the CPIcore. In Table 4, Panel A, we also find that for CPIcore the UCSV model provides the lowest RMSFE for both forecasting horizons. The gains of UCSV appear stronger for h=1, which is consistent with the results for PCEcore. Hence the relative RMSFEs for different models are again reported vis-à-vis the UCSV. In addition, in Panel A we find that for h=4, combinations of the traditional FAR models, based on either 2DMSFE or MMA, improve upon the UCSV by 53% and 69%, respectively. Therefore, forecast combinations of FAR models appear to be more successful for the CPIcore than PCEcore for h=4, during our sample period.

The results in Panels B and C of Table 4 report the relative RMSFEs vis-à-vis the UCSV from the combinations of the 90 daily predictors and 10 daily factors, respectively. We find the following results:

First, the forecasting gains measured by RMSFE are higher for h=4 than h=1 for CPIcore inflation using all three different methods of forecasting combination (Mean, 2DMSFE and MMA) reported in Table 4. These results also hold for all categories of models estimated as listed in the first column of Table 4 and for all five classes of daily predictors and daily factors and asset classes presented in Table 7. We note that this result also holds for PCEcore and to other measures of forecast combinations namely Median, TRMEAN, DMSFE and Best, reported in Table 8.

Second, the information of the 90 daily predictors and 10 daily factors (presented in Panels B and C, respectively) turns out to be useful for forecasting CPIcore inflation especially for h=4 using either the 2DMSFE or MMA methods, in either traditional models like (F)ADL or (F)ADL-MIDAS models (with or without leads) since it improves the RMSFE vis-à-vis the UCSV model, ranging from 24% (2DMSFE) to 59% (MMA). Hence the information from the predictors with flat or data-driven weights improves forecasting performance relative to all the benchmark models. However the evidence in favor of using data-driven weights in the MIDAS models with no leads is weak vis-à-vis the flat weighting scheme for CPIcore. This result is also consistent with the PCEcore evidence. At h=4 while MMA combinations favor (F) ADL-MIDAS models, the 2DMSFE shows relatively mixed evidence.

Third, we find that in general, including quarterly factors does not always improve forecasts of CPIcore inflation for either forecasting horizon, for all combination methods. This is also in agreement with the PCEcore results. A notable exception for CPIcore inflation is the case of combinations with the 2DMSFE of traditional quarterly FADL models at h=4 which yields relative RMSFE equal to 24%. In addition we find that for CPIcore forecasts, the 2DSMFE and MMA combination methods provide higher relative gains compared to the simple Mean combination method across both the 90 predictors and 10 daily factors and across all classes of models presented in Table 4. More importantly, the largest forecasting gains are in general obtained from the combinations of MIDAS models with daily leads and in particular the ADL-MIDAS ($J_X = 2$) models across all h.

Fourth, for h=1 whether we combine either the daily predictors or daily factors in MIDAS models with leads yield very similar RMSFEs. However, for h=4 we find that the 2DMSFE and MMA methods yield opposite results. Namely for h=4 the 2DMSFE combination approach shows that the 90 daily predictors yield the lower relative RMSFE using the FADL model (24%) followed by the FADL-MIDAS ($J_X = 0$) and ADL-MIDAS ($J_X = 2$), with 27% and 28% relative RMSFEs, respectively. In contrast, the MMA method and h=4, suggests the opposite, namely that the daily factors yield the relatively lowest RMSFE. Overall, unlike the question as to whether the leading information in daily factors or the 90 daily predictors improves CPIcore forecasts depends on the combination method used. This is in contrast to the GDP growth and PCEcore results discussed above which showed it is the daily factors in MIDAS models with leads can improve forecasting performance.

We now turn to Table 7 in order to obtain a deeper understanding as to the classes of assets that provide the highest forecasting gains. Using the 2DMSFE we find that for both h=1 and 4 the forecast combinations of the 90 daily predictors are superior to those of the daily factors for CPIcore inflation. In particular, for h=4 the RMSFE gains are driven from the combinations of the following blocks of assets: the 7 daily FX series, the 16 corporate risk series and to a less extend to the 40 commodities, found in Table A1. Note that among the best predictors for CPIcore inflation are the Canadian$/US$, the 1-month LIBOR and gold prices, whereas the best factors are $F^D_{ALL,1}$ an $F^D_{ALL,3}$. We obtain similar results for PCEcore for h=4 and the FX and corporate risk blocks of daily assets using all combination methods as well as some of the best daily predictors (Canadian$/US$ and $F^D_{ALL,3}$).

6.3 Forecast Evaluation

Sections 6.1 and 6.2 have demonstrated that MIDAS models can effectively exploit daily financial information giving rise to substantial forecasting gains for forecasting inflation and economic activity. Although it is difficult to evaluate directly the forecasting gains by means of standard evaluation tools (e.g. Diebold and Mariano (1995)) due to the small number of out-of sample forecasts relative to the random sampling variation, we can exploit the cross-sectional dimension of our panel. We consider 2DMSE forecast combinations for each asset to obtain a balanced panel of out-of sample forecasts over the 90 predictors.[16] We evaluate these forecasts using a graphical analysis as well as formal testing.

Figures 8-9 present the cross-sectional distribution of RMSFEs for GDP growth for h=1 and 4. Figures 10- 11 and Figures 12-13 display the corresponding figures for PCEcore and CPIcore Inflation, respectively. The dashed line refers to the absolute RMSFE of the RW. Box plots with tighter boxes indicate less forecast uncertainty. The interquartile range, which is represented by the width of the box can be viewed as a rough measure of uncertainty of the forecast. Interestingly, the box of FADL-MIDAS with leads lies below the lower whisker of the corresponding FADL model for GDP growth. Furthermore, MIDAS models with quarterly factors (FADL-MIDAS) appear to be more important for GDP growth than CPIcore. Another interesting observation is that the distribution of the RMSFEs appears to be generally left-skewed for GDP growth and right-skewed for CPIcore Inflation. In the case of GDP growth, MIDAS models appear to have a longer tail, implying that the MIDAS models dominate among the best performing models. Overall, the conclusions from these box plots are remarkably consistent with the findings in sections 6.1 and 6.2. MIDAS models with leads and sometimes even MIDAS model with no-leads can provide substantial forecasting gains.

[16]We also considered the Mean and the MMA forecast combinations for each asset but the results appeared to be qualitatively similar.

Our testing strategy employs panel versions of the Diebold-Mariano test, the classic SumDifference test of Granger and Huang (1997). Consider the out-of sample errors for asset i $e_{i,t+h|t} = y_{t+h} - \widehat{y}_{i,t+h|t}$ and the square loss function $L(y_{t+h}, \widehat{y}_{i,t+h|t}) = \widehat{e}^2_{i,t+h|t}$. Then the difference between the square losses of FADL-MIDAS and FADL using the time t forecast is given by $d_{i,t+h} = L^{ADL-MIDAS}(y_{t+h}, \widehat{y}_{i,t+h|t}) - L^{ADL}(y_{t+h}, \widehat{y}_{j,t+h|t})$. Then the Panel DM test statistic can be simply computed by $\overline{DM}_h = \sum_{i=1}^{n} DM_{i,h}/\sqrt{n}$. This is equivalent to running the regression of the standard Diebold-Mariano statistic, $DM_{i,h}$, for asset unit i on a constant. We also consider robust versions of this test that allow for group effects defined by the 5 classes of assets. The distribution of this statistic is bootstrapped with replacement from the asset based empirical distribution of Diebold - Mariano statistics, $DM_{1,h}, ..., DM_{n,h}$, in order to allow for the fact that forecasts errors are at most (h - 1)-dependent.

The classic Sum-Difference considers both the sum and the difference of square error losses between FADL-MIDAS and FADL. Consider the sum $s_{i,t+h} = L^{FADL-MIDAS}(y_{t+h}, \widehat{y}_{i,t+h|t}) + L^{FADL}(y_{t+h}, \widehat{y}_{j,t+h|t})$. Then, the null of equal predictive ability is equivalent to testing the null $H_0 : \gamma = 0$ using a panel regression with fixed and/or time effects

$$s_{i,t} = \alpha_i + \beta_t + \gamma d_{i,t} + u_{i,t}.$$

Table 10 presents the results for forecast evaluation of the predictive gains of FADL-MIDAS($J_X = 2$) over FADL. We present the Theil's U statistic as a ratio of the means of RMSFEs of ADL-MIDAS($J_X = 2$) models over the 90 predictors over the corresponding mean of ADL models, the panel DM statistic, its bootstrap p-value, and panel sum-difference tests. The results appear to be consistent with the evidence in Figures 4a,b and 5a,b.

7 Conclusion

In this paper we show that there are substantial forecasting gains for forecasting inflation and economic activity using higher frequency/daily financial data and (F)ADL-MIDAS models. Short summary of results.

We show that daily variables that appear to have useful information especially for forecasting both economic activity and inflations that goes beyond the information included in the quarterly factors. More importantly we show how MIDAS models can efficiently incorporate leading information from daily predictors and provide accurate forecasts, especially when these models incorporate real-time information using daily leads within the quarter.

Finally, the daily factors appear to have useful information for forecasting inflation and especially economic activity beyond the information included in the quarterly factors. Investors and policy institutions are often faced with a large cross-sectional information of possible leading indicators. To summarize this vast information we provide results based on combinations of ten daily factors from the cross section of 988 assets. MIDAS models can efficiently incorporate this information and provide accurate forecasts, especially when these models incorporate real-time information using daily leads within the quarter. Last but not least our daily financial factors are of independent interest and can be applied in many different areas of financial modeling.

Figure 1: 1st Daily Factor from All the 988 Daily Predictors

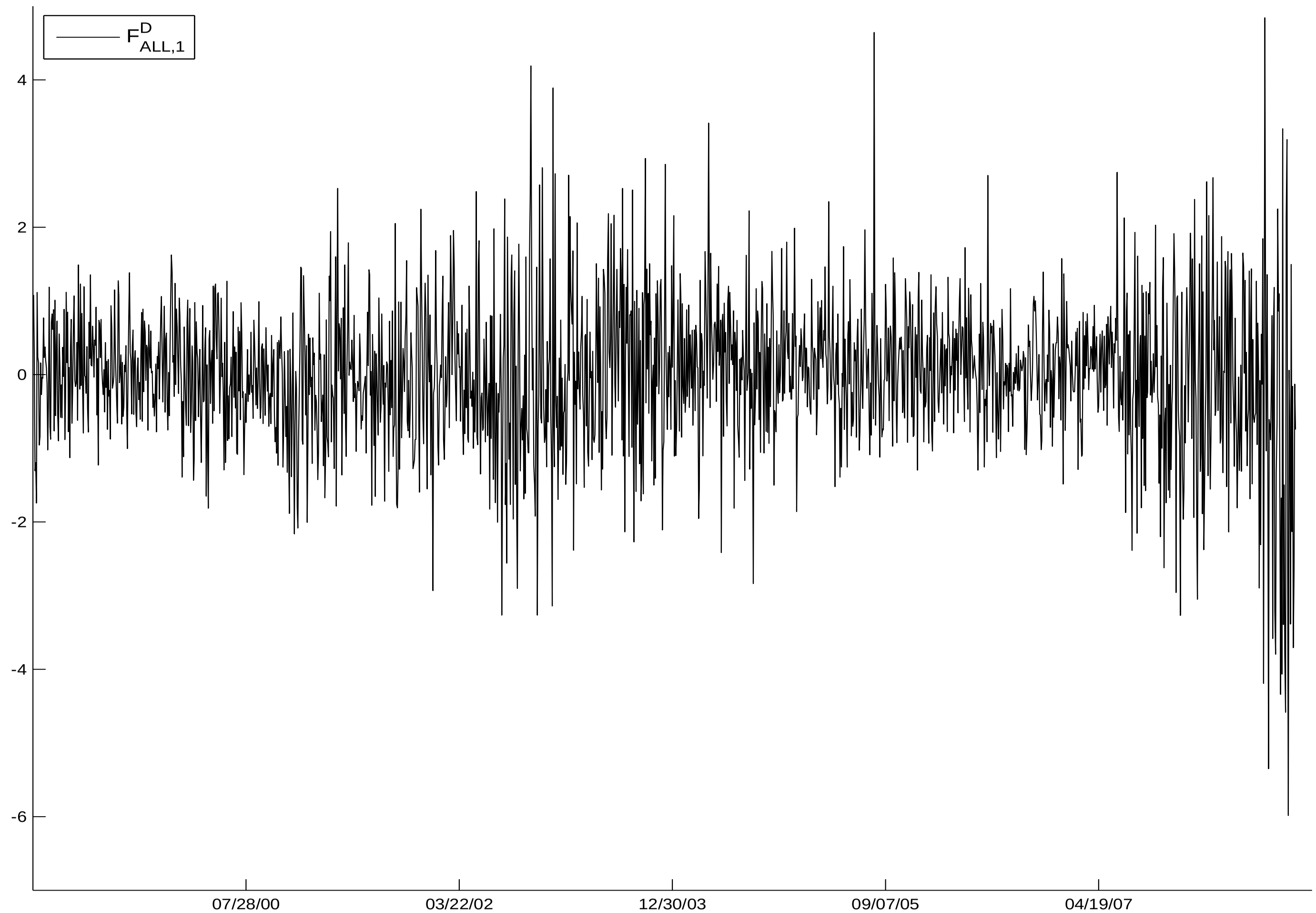

Figure 2: 2nd Daily Factor from All the 988 Daily Predictors

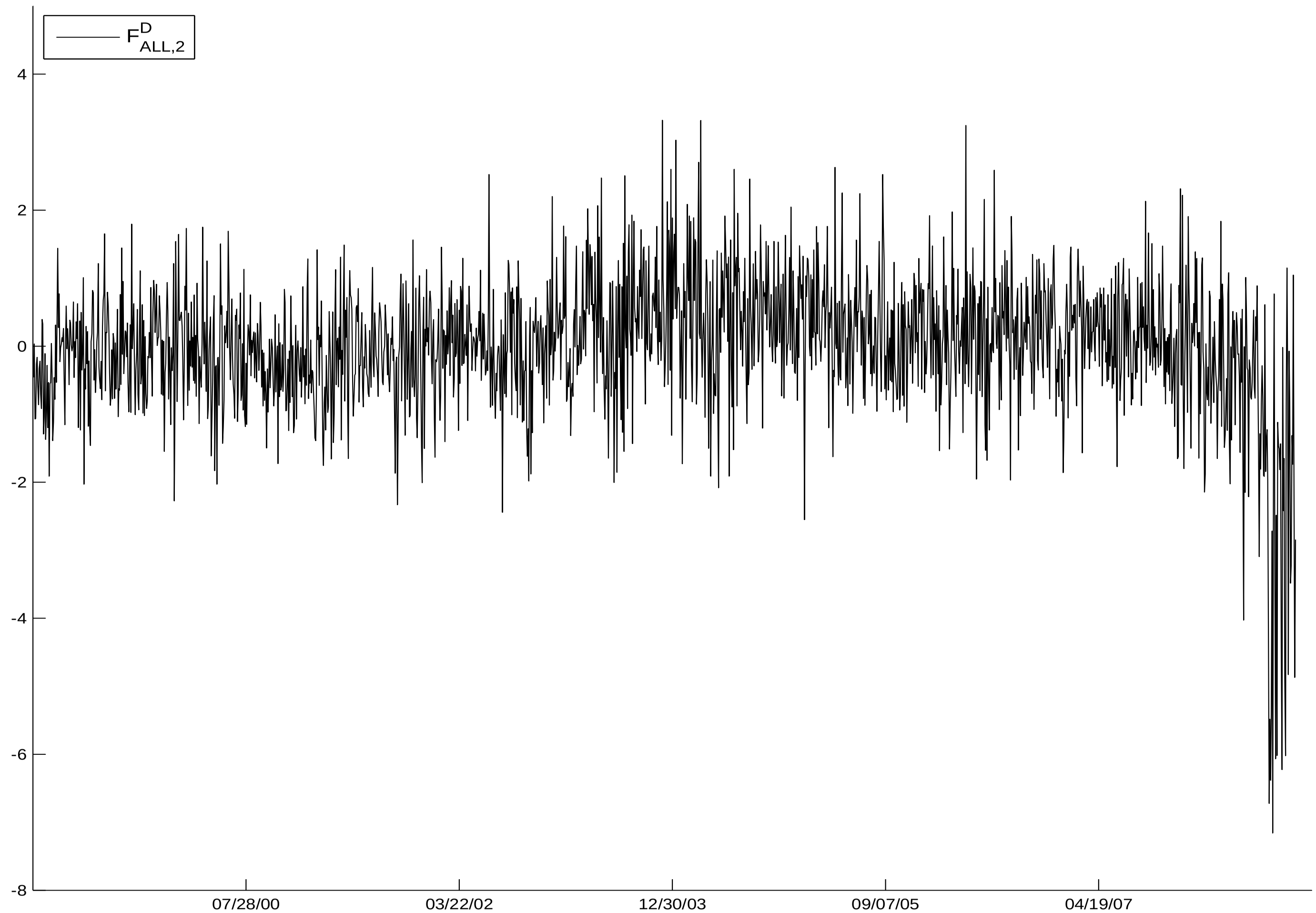

Figure 3: 3rd Daily Factor from All the 988 Daily Predictors

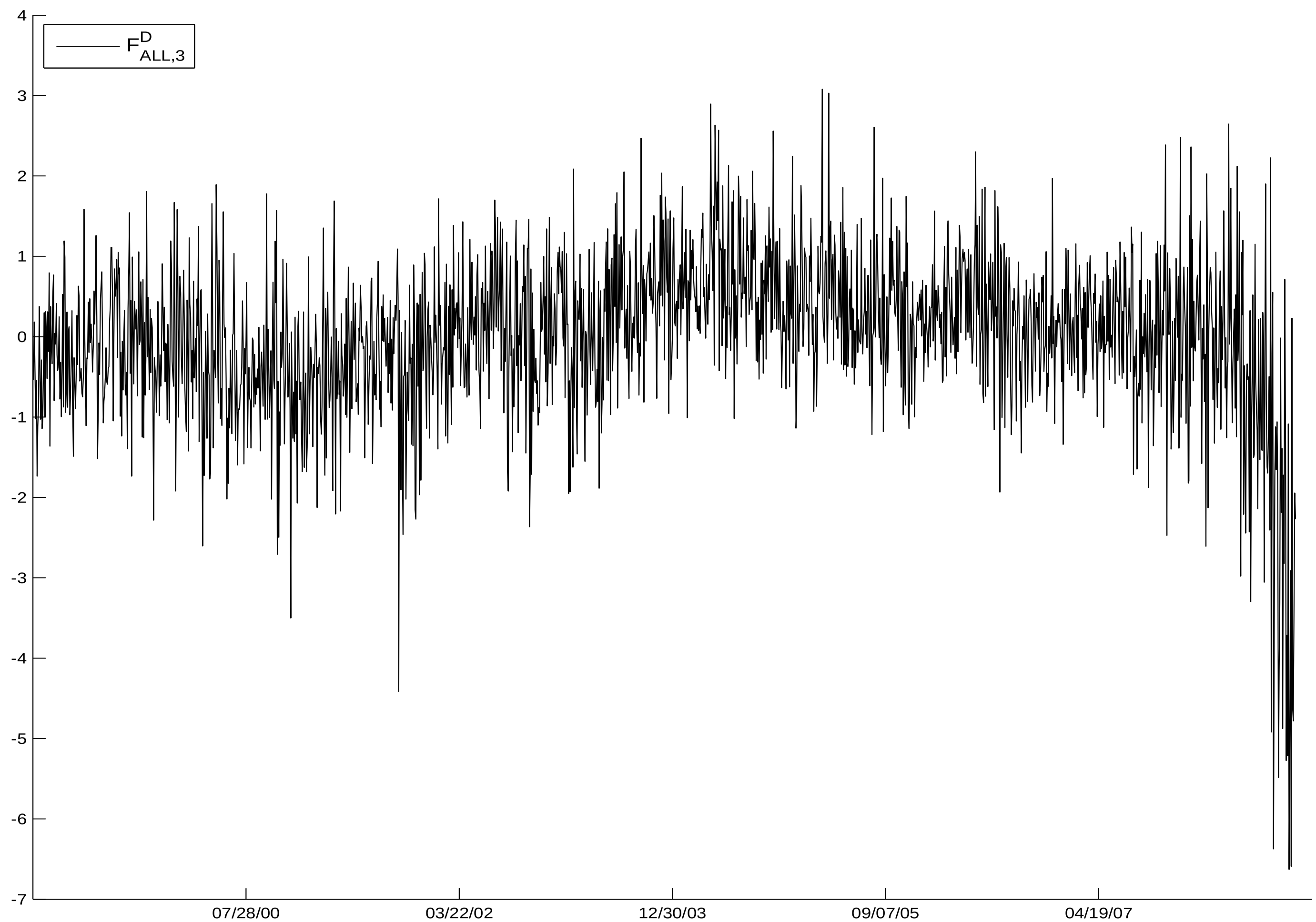

Figure 4: 1st Daily Factor from the class of Commodities

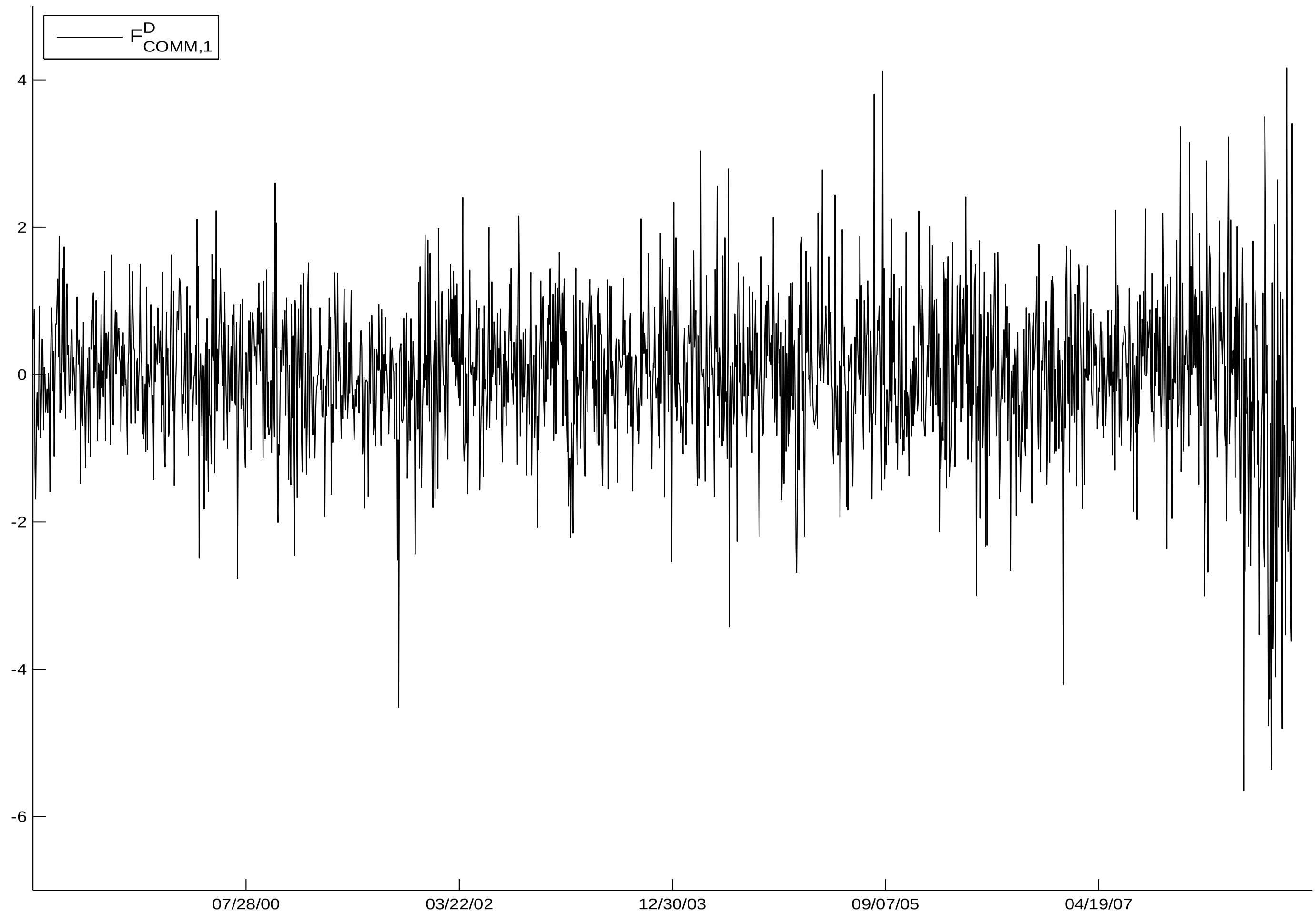

Figure 5: 1st Daily Factor from the class of Corporate Risk

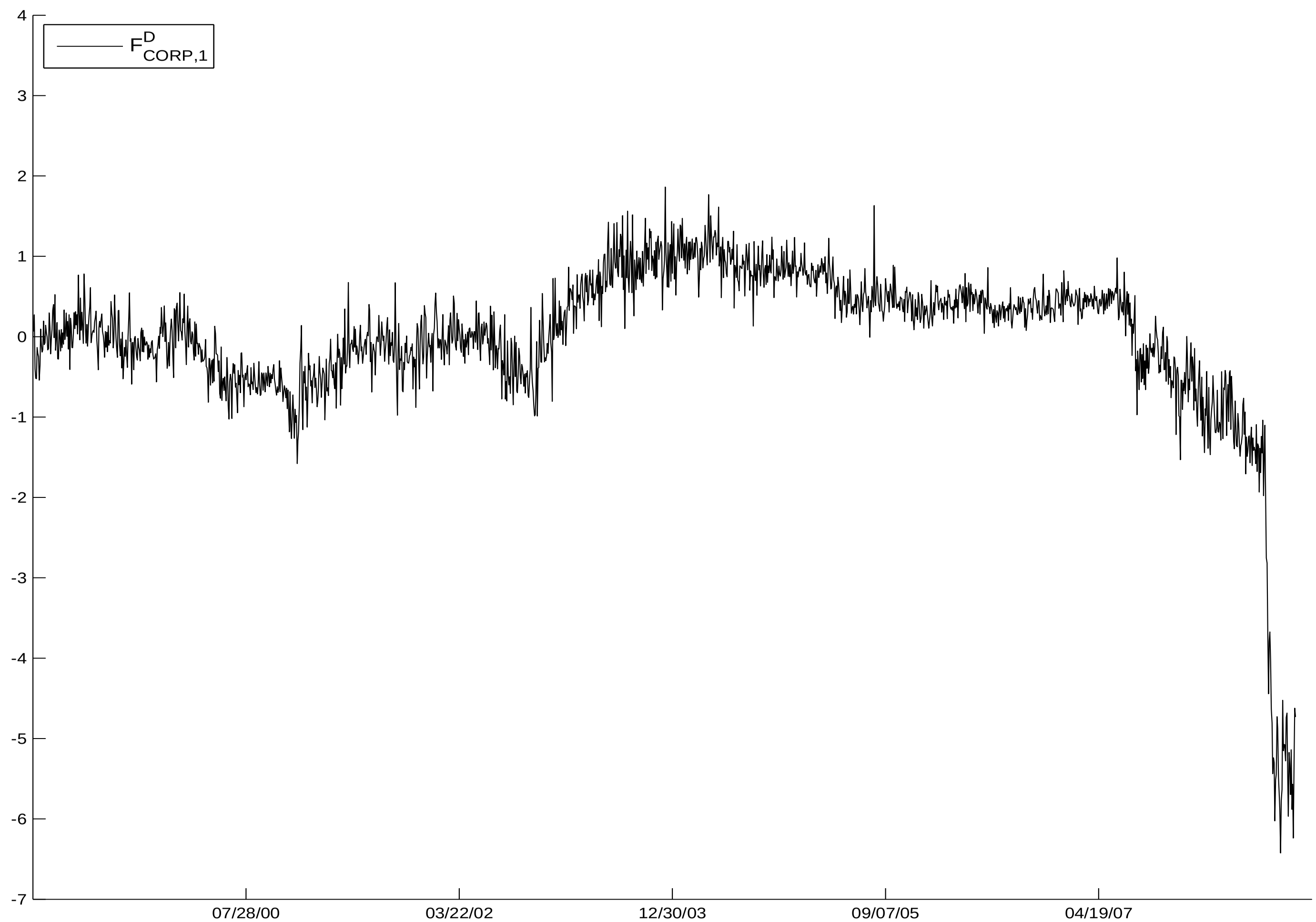

Figure 6: 1st Daily Factor from the class of Equities

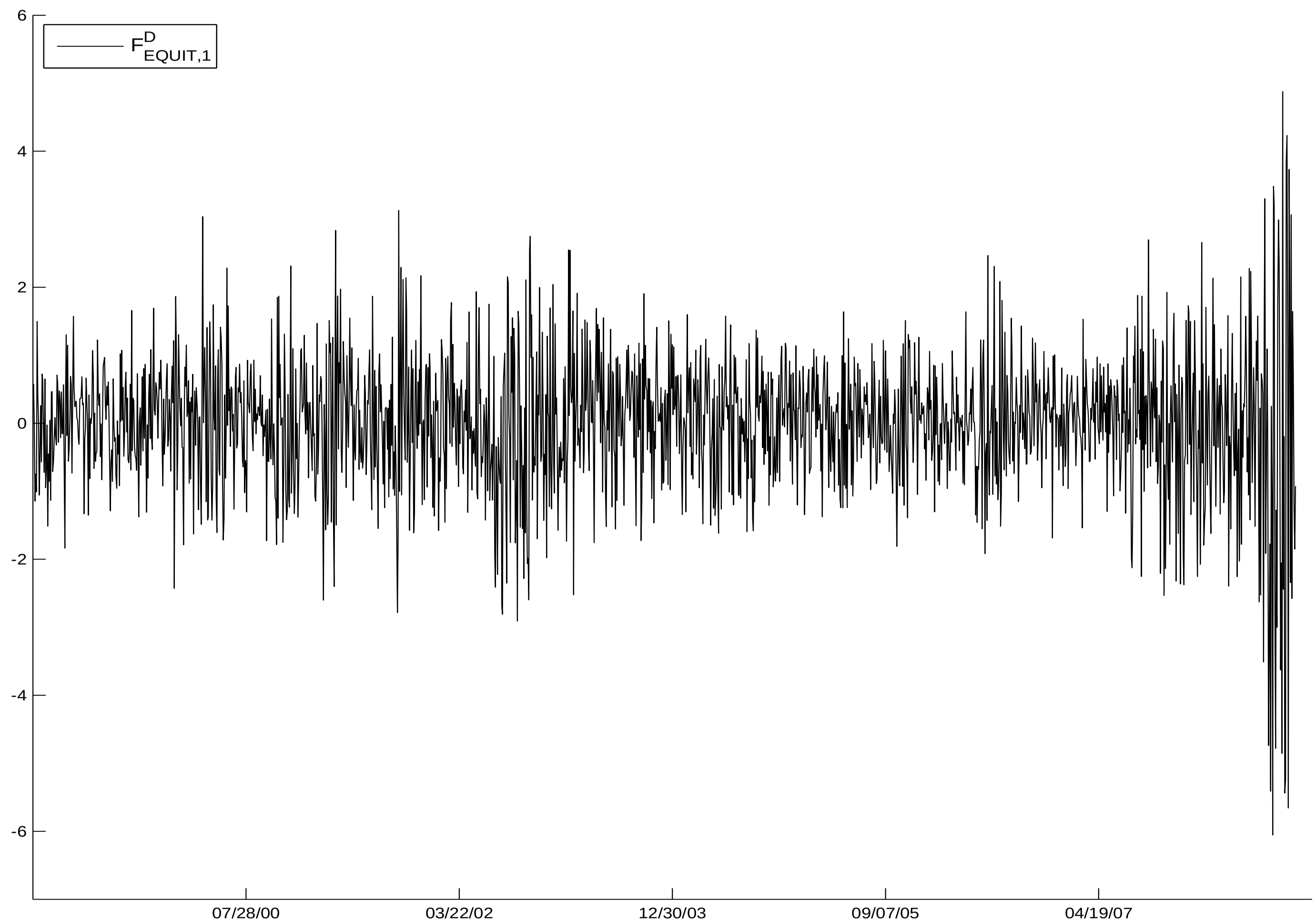

Figure 7: 1st Daily Factor from the class of Government Securities

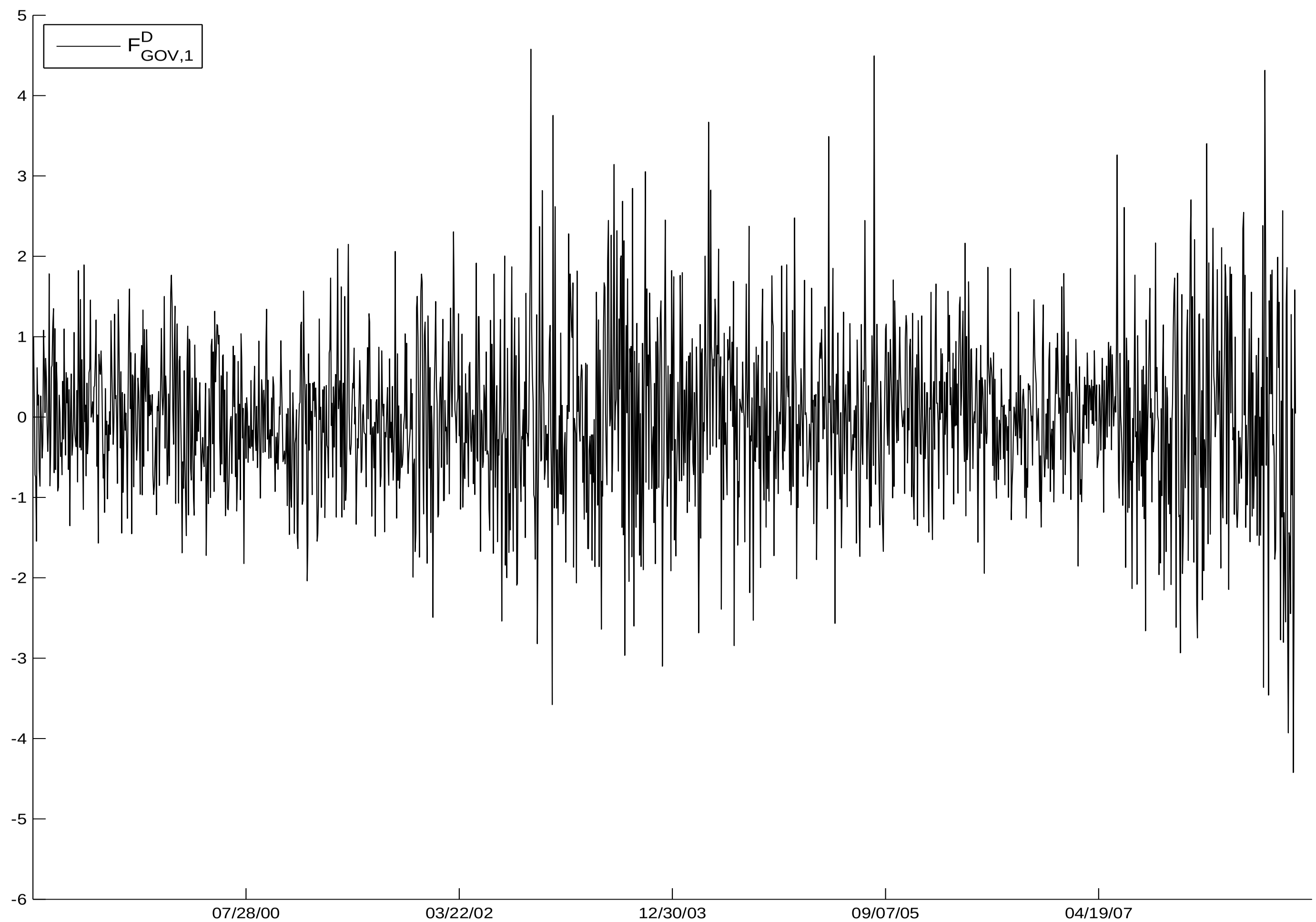

Figure 8: Box Plots for GDP Growth for h = 1

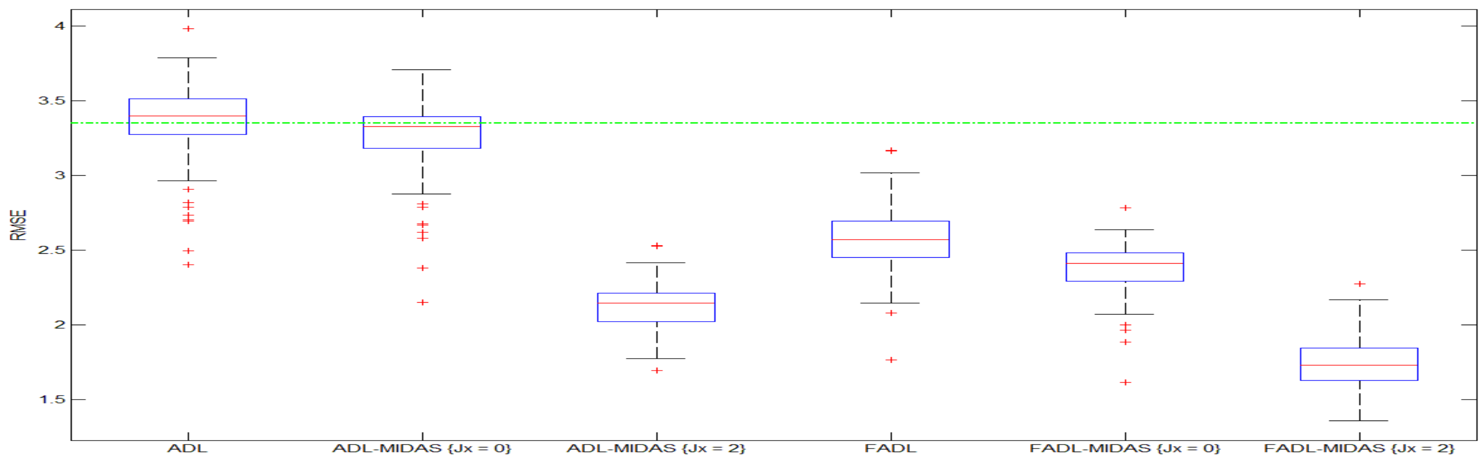

Figure 9: Box Plots for GDP Growth for h = 4

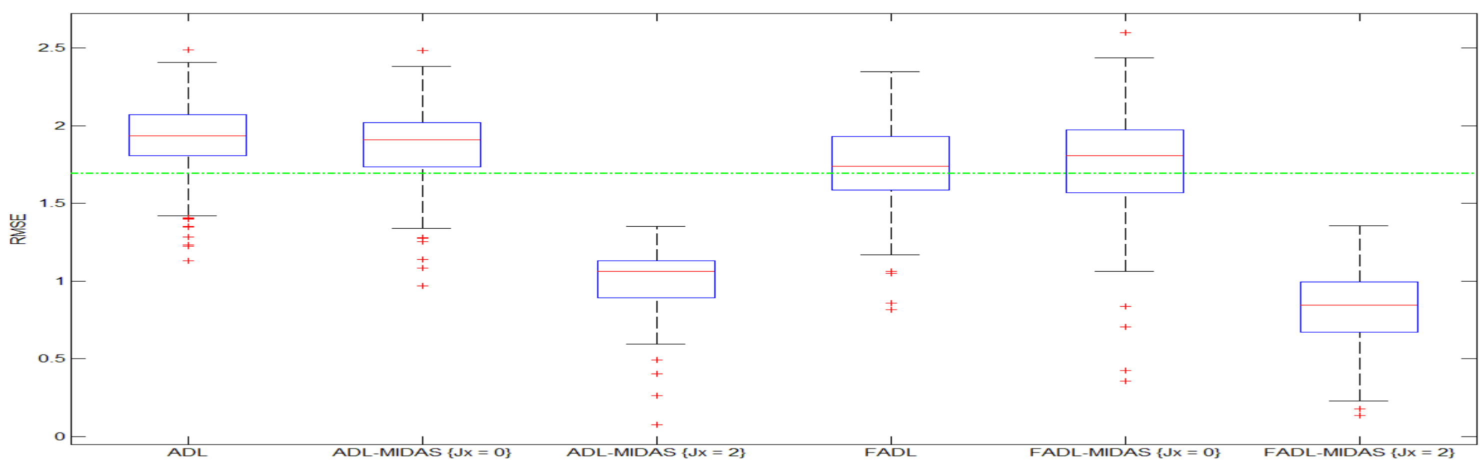

Figure 10: Box Plots for PCEcore Inflation for h = 1

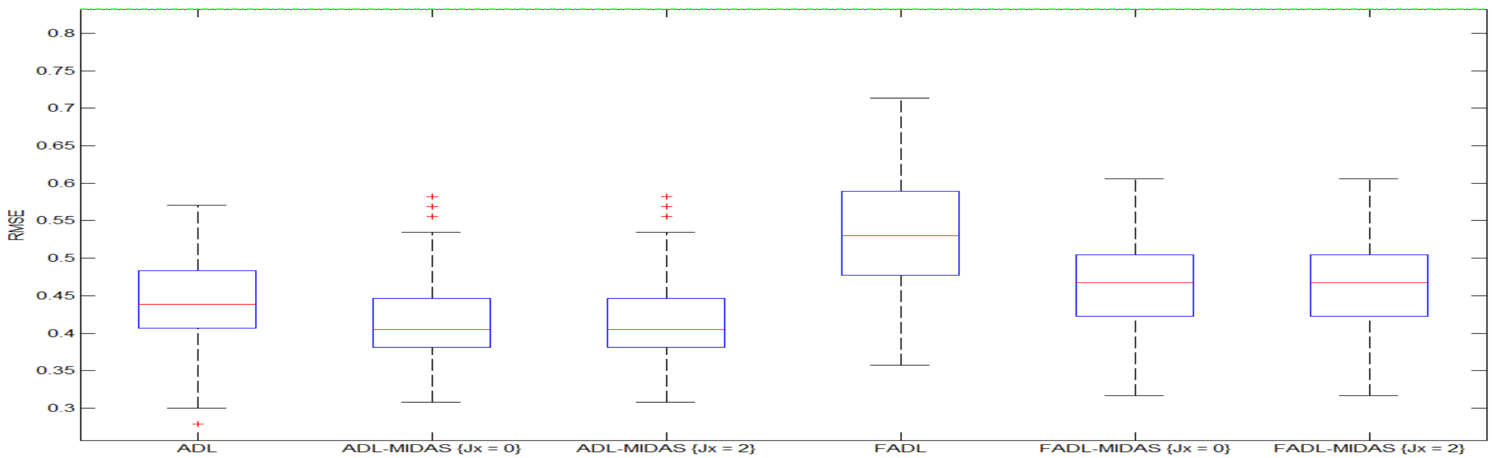

Figure 11: Box Plots for PCEcore Inflation for h = 4

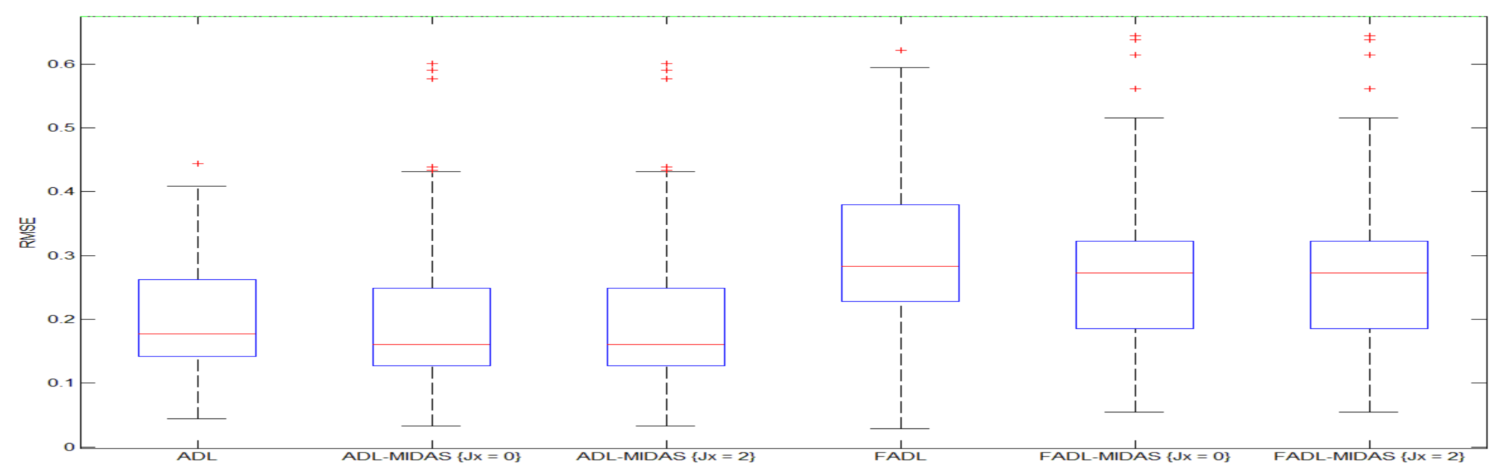

Figure 12: Box Plots for CPIcore Inflation for h = 1

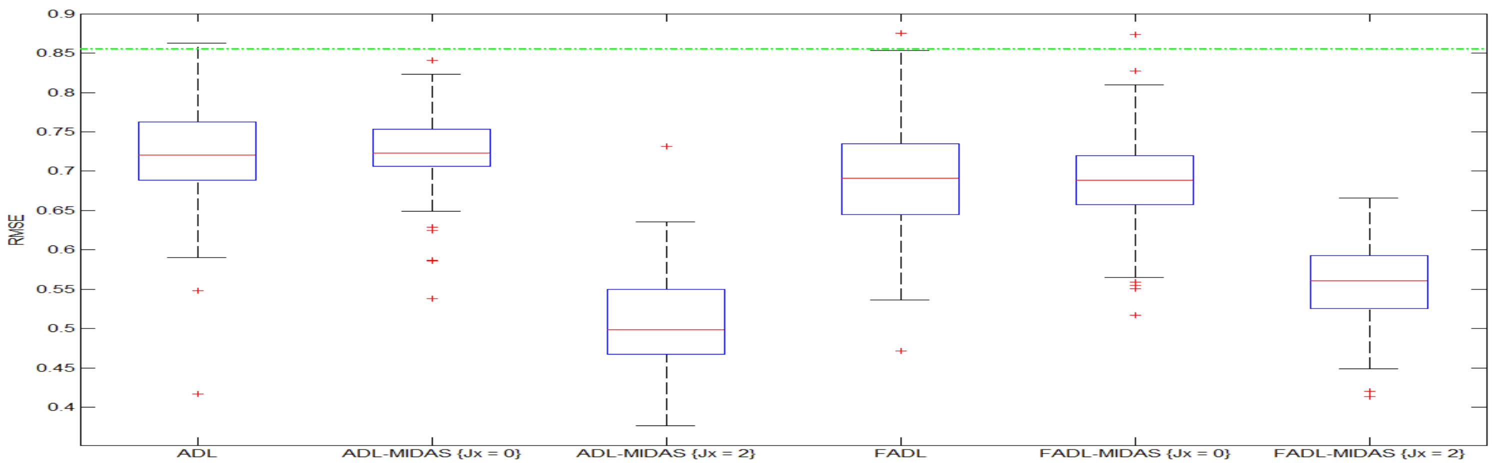

Figure 13: Box Plots for CPIcore Inflation for h = 4

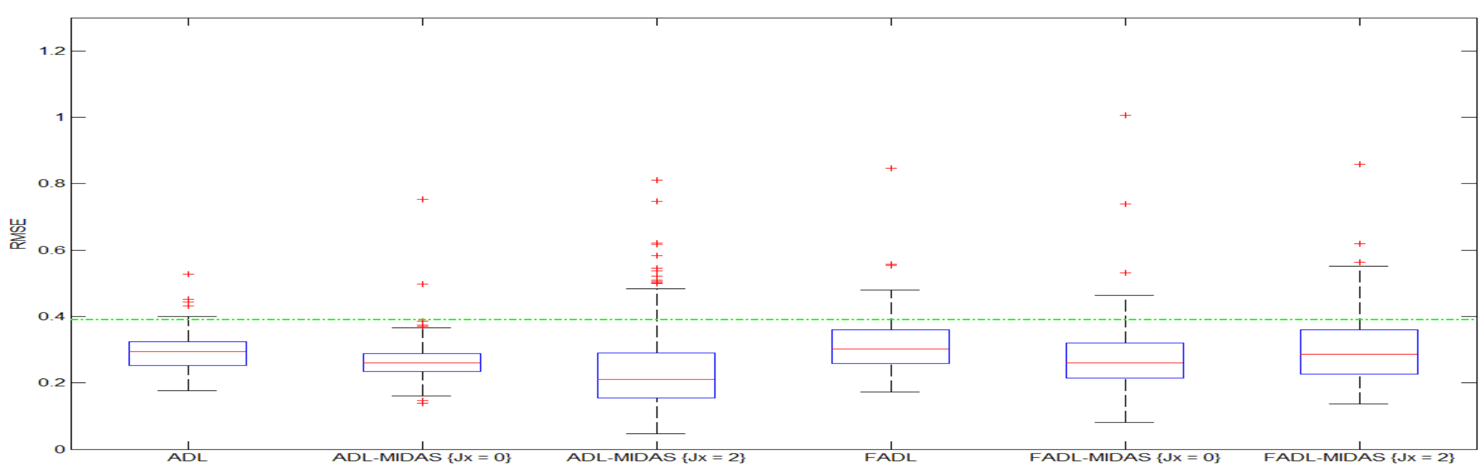

Table 1: Analysis of Daily Factors

Table 1 provides an analysis of the daily factors. Panel A shows the standardized eigenvalues for *all* Predictors as well as for the five classes of assets. Column 1 presents the results for all 988 predictors while Columns 2-6 present the eigenvalues for Commodities, Corporate Risk, Equity, Foreign Exchange, and Government Securities. Panel B shows the loads of each class of assets to the 10 factors extracted from *all* 988 predictors.

Class of Assets (j)	ALL (1)	COMM (2)	CORP (3)	EQUIT (4)	FX (5)	GOV (6)
Panel A						
Percentage of Explained Variation: Standardized Eigenvalues						
Daily Factors						
$F^D_{j,1}$	0.29	0.50	0.35	0.72	0.56	0.49
$F^D_{j,2}$	0.17	0.16	0.30	0.07	0.12	0.17
$F^D_{j,3}$	0.14	0.09	0.15	0.06	0.07	0.10
$F^D_{j,4}$	0.11	0.05	0.06	0.04	0.05	0.07
$F^D_{j,5}$	0.09	0.05	0.04	0.02	0.04	0.06
$F^D_{j,6}$	0.07	0.04	0.03	0.02	0.04	0.04
$F^D_{j,7}$	0.04	0.03	0.02	0.02	0.04	0.03
$F^D_{j,8}$	0.03	0.03	0.02	0.02	0.03	0.02
$F^D_{j,9}$	0.03	0.03	0.02	0.02	0.03	0.02
$F^D_{j,10}$	0.02	0.02	0.01	0.01	0.03	0.01
Panel B						
Sum of Square Loadings of $F^D_{ALL,j}, j = 1, 2, .., 10$ *for the 5 Classes of Assets*						
$F^D_{ALL,1}$		0.31	0.16	0.17	0.00	0.36
$F^D_{ALL,2}$		0.21	0.17	0.43	0.02	0.17
$F^D_{ALL,3}$		0.17	0.33	0.18	0.01	0.31
$F^D_{ALL,4}$		0.25	0.44	0.16	0.02	0.14
$F^D_{ALL,5}$		0.15	0.41	0.04	0.02	0.39
$F^D_{ALL,6}$		0.25	0.29	0.08	0.22	0.16
$F^D_{ALL,7}$		0.24	0.04	0.04	0.58	0.09
$F^D_{ALL,8}$		0.21	0.19	0.04	0.04	0.53
$F^D_{ALL,9}$		0.23	0.06	0.12	0.04	0.56
$F^D_{ALL,10}$		0.22	0.31	0.05	0.08	0.35

Table 2: Forecast Combinations for GDP growth

Table 2 presents RMSFEs of forecast combinations for GDP growth relative to the RMSFE of RW for 1- and 4-step ahead forecasts. The first row refers to RW, which is presented in absolute RMSFE. We present the Mean forecast, the 2DMSFE with $\delta = 0.9$, and MMA. All models are summarized in Table A3. The Entries below one imply improvements compared to the benchmark. The results on daily predictors refer to the subset of 90 predictors while the results for the daily factors are based on the larger set of 988 variables. The estimation period is 1999:Q1 to 2005:Q4 and the forecasting period is 2006:Q1 + h to 2008:Q4 - h.

	Mean		2DMSFE		MMA	
Forecast Horizon	1	4	1	4	1	4
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Benchmarks					
RW	3.35	1.69	3.35	1.69	3.35	1.69
AR	0.96	1.05	1.00	1.16	1.01	1.16
FAR	0.77	1.08	0.73	0.95	0.79	1.15
	Panel B: Daily Predictors					
ADL	0.96	1.02	0.92	0.89	1.01	1.14
FADL	0.76	0.97	0.67	0.74	0.79	1.06
ADL-MIDAS ($J_X = 0$)	0.94	1.01	0.87	0.87	0.98	1.13
FADL-MIDAS ($J_X = 0$)	0.72	1.00	0.64	0.52	0.75	1.08
ADL-MIDAS ($J_X = 2$)	0.61	0.55	0.55	0.24	0.64	0.61
FADL-MIDAS ($J_X = 2$)	0.53	0.54	0.45	0.26	0.55	0.52
	Panel C: Daily Factors					
ADL	0.92	0.91	0.87	0.95	0.97	1.02
FADL	0.76	0.87	0.71	0.69	0.80	0.96
ADL-MIDAS ($J_X = 0$)	0.91	0.94	0.85	1.00	0.95	1.04
FADL-MIDAS ($J_X = 0$)	0.71	0.95	0.65	0.93	0.75	1.03
ADL-MIDAS ($J_X = 2$)	0.57	0.40	0.49	0.30	0.61	0.45
FADL-MIDAS ($J_X = 2$)	0.52	0.44	0.45	0.33	0.55	0.43

Table 3: Forecast Combinations for PCEcore

Table 3 presents RMSFEs of forecast combinations for PCEcore Inflation relative to the RMSFE of UCSV for 1- and 4-step ahead forecasts. The first two rows refer to UCSV and AO, which are presented in absolute RMSFE. We present the Mean forecast, the 2DMSFE with $\delta = 0.9$, and MMA. All models are summarized in Table A3. Entries below one imply improvements compared to the benchmark. The results on daily predictors refer to the subset of 90 predictors while the results for the daily factors are based on the larger set of 988 variables. The estimation period is 1999:Q1 to 2005:Q4 and the forecasting period is 2006:Q1 + h to 2008:Q4 - h.

	Mean		2DMSFE		MMA	
Forecast Horizon	1	4	1	4	1	4
			Panel A: Benchmarks			
UCSV	0.65	0.29	0.65	0.29	0.65	0.29
AO	1.08	0.29	1.08	0.29	1.08	0.29
AR	1.03	0.77	0.97	0.85	0.98	0.86
FAR	1.00	1.02	0.93	0.77	0.99	0.94
			Panel B: Daily predictors			
ADL	0.98	0.99	0.80	0.64	0.98	1.11
FADL	0.96	1.13	0.58	0.37	0.96	1.11
ADL-MIDAS ($J_X = 0$)	0.98	0.86	0.85	0.57	0.97	0.97
FADL-MIDAS ($J_X = 0$)	0.95	1.07	0.70	0.42	0.94	1.05
ADL-MIDAS ($J_X = 2$)	0.72	0.68	0.53	0.23	0.65	0.79
FADL-MIDAS ($J_X = 2$)	0.86	1.32	0.61	0.48	0.81	1.34
			Panel C: Daily factors			
ADL	1.00	1.00	0.76	0.54	1.00	1.09
FADL	1.00	1.21	0.62	0.32	0.99	1.14
ADL-MIDAS ($J_X = 0$)	1.00	0.89	0.88	0.58	1.00	1.00
FADL-MIDAS ($J_X = 0$)	0.96	1.02	0.78	0.50	0.95	1.00
ADL-MIDAS ($J_X = 2$)	0.69	0.73	0.48	0.42	0.63	0.85
FADL-MIDAS ($J_X = 2$)	0.85	1.27	0.62	0.71	0.79	1.24

Table 4: Forecast Combinations for CPIcore

Table 4 presents RMSFEs of forecast combinations for CPIcore Inflation relative to the RMSFE of UCSV for 1- and 4-step ahead forecasts. The first two rows refer to UCSV and AO, which are presented in absolute RMSFE. We present the Mean forecast, the 2DMSFE with $\delta = 0.9$, and MMA. All models are summarized in Table A3. Entries below one imply improvements compared to the benchmark. The results on daily predictors refer to the subset of 90 predictors while the results for the daily factors are based on the larger set of 988 variables. The estimation period is 1999:Q1 to 2005:Q4 and the forecasting period is 2006:Q1 + h to 2008:Q4 - h.

	Mean		2DMSFE		MMA	
Forecast Horizon	1	4	1	4	1	4
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Benchmarks			
UCSV	0.73	0.35	0.73	0.35	0.73	0.35
AO	1.72	0.37	1.72	0.37	1.72	0.37
AR	1.08	0.70	1.00	0.75	1.01	0.78
FAR	1.02	0.93	0.93	0.53	0.97	0.69
			Panel B: Daily Predictors			
ADL	1.01	0.69	0.87	0.54	0.97	0.72
FADL	0.95	1.00	0.81	0.24	0.93	0.69
ADL-MIDAS ($J_X = 0$)	1.05	0.66	0.92	0.42	1.00	0.65
FADL-MIDAS ($J_X = 0$)	1.00	0.95	0.83	0.27	0.95	0.67
ADL-MIDAS ($J_X = 2$)	0.82	0.62	0.61	0.28	0.69	0.60
FADL-MIDAS ($J_X = 2$)	0.87	1.08	0.68	0.55	0.78	0.89
			Panel C: Daily Factors			
ADL	1.05	0.66	0.96	0.57	1.01	0.72
FADL	0.99	0.87	0.89	0.73	0.95	0.72
ADL-MIDAS ($J_X = 0$)	1.07	0.69	0.97	0.51	1.01	0.68
FADL-MIDAS ($J_X = 0$)	1.01	1.01	0.84	0.70	0.95	0.74
ADL-MIDAS ($J_X = 2$)	0.81	0.68	0.62	0.41	0.70	0.59
FADL-MIDAS ($J_X = 2$)	0.87	1.01	0.72	0.53	0.77	0.77

Table 5: Blockwise Analysis of Forecast Combinations for GDP growth

Table 5 presents a blockwise analysis of RMSFEs of forecast combinations based on 2DMSFE forecast with $\delta = 0.9$ for GDP growth relative to the RMSFE of RW for 1- and 4-step ahead forecasts. Columns (1)-(2) refer to the results based on all 90 predictors (for the daily predictors) or 988 predictors (for the daily factors). Pairs of Columns (3)-(4), (5)-(6),(7)-(8), (9)-(10), and (11)-(12) refer to subsets of variables based the classes of Commodities, Corporate Risk, Equities, Exchange Rates, and Government Securities, respectively. All models are summarized in Table A3. The notation (F) is used to denote that the forecast combination did not condition on including or excluding the quarterly factors but rather attached weights across ADL and F-ADL models. Entries below one imply improvements compared to the benchmark. The estimation period is 1999:Q1 to 2005:Q4 and the forecasting period is 2006:Q1 + h to 2008:Q4 - h.

	ALL		COMMOD		CORPRSK		EQUIT		FX		GOVSEC	
Forecast Horizon	1	4	1	4	1	4	1	4	1	4	1	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
							Panel A: Daily Predictors					
(F)-ADL	0.73	0.81	0.78	0.94	0.73	0.60	0.76	1.05	0.68	1.18	0.77	0.88
(F)-ADL-MIDAS ($J_X = 0$)	0.70	0.66	0.73	0.89	0.70	0.37	0.73	1.05	0.68	1.22	0.73	0.94
(F)-ADL-MIDAS ($J_X = 2$)	0.46	0.24	0.48	0.47	0.44	0.12	0.42	0.20	0.54	0.21	0.50	0.36
F-ADL	0.67	0.74	0.71	0.89	0.68	0.54	0.71	1.00	0.62	1.12	0.70	0.87
F-ADL-MIDAS ($J_X = 0$)	0.64	0.52	0.66	0.78	0.67	0.29	0.67	1.01	0.61	1.21	0.65	0.95
F-ADL-MIDAS ($J_X = 2$)	0.45	0.26	0.47	0.41	0.45	0.24	0.44	0.18	0.51	0.08	0.48	0.39
							Panel B: Daily Factors					
(F)-ADL	0.75	0.77	0.81	0.99	0.64	0.82	0.83	0.86	0.63	0.90	0.76	0.90
(F)-ADL-MIDAS ($J_X = 0$)	0.70	0.96	0.76	1.09	0.61	0.90	0.77	0.98	0.64	1.00	0.70	0.92
(F)-ADL-MIDAS ($J_X = 2$)	0.43	0.31	0.47	0.41	0.44	0.38	0.48	0.11	0.43	0.13	0.47	0.44
F-ADL	0.71	0.69	0.74	0.94	0.58	0.76	0.77	0.77	0.57	0.84	0.69	0.87
F-ADL-MIDAS ($J_X = 0$)	0.65	0.93	0.69	1.06	0.55	0.85	0.70	0.90	0.58	0.97	0.63	0.84
F-ADL-MIDAS ($J_X = 2$)	0.45	0.33	0.46	0.33	0.42	0.35	0.48	0.09	0.41	0.10	0.45	0.37

Table 6: Blockwise Analysis of Forecast Combinations for PCEcore Inflation

Table 6 presents a blockwise analysis of RMSFEs of forecast combinations based on 2DMSFE forecast with $\delta = 0.9$ for PCEcore Inflation relative to the RMSFE of UCSV for 1- and 4-step ahead forecasts. Columns (1)-(2) refer to the results based on all 90 predictors (for the daily predictors) or 988 predictors (for the daily factors). Pairs of Columns (3)-(4), (5)-(6),(7)-(8), (9)-(10), and (11)-(12) refer to subsets of variables based the classes of Commodities, Corporate Risk, Equities, Exchange Rates, and Government Securities, respectively. All models are summarized in Table A3. The notation (F) is used to denote that the forecast combination did not condition on including or excluding the quarterly factors but rather attached weights across ADL and F-ADL models. Entries below one imply improvements compared to the benchmark. The estimation period is 1999:Q1 to 2005:Q4 and the forecasting period is 2006:Q1 + h to 2008:Q4 - h.

	ALL		COMMOD		CORPRSK		EQUIT		FX		GOVSEC	
Forecast Horizon	1	4	1	4	1	4	1	4	1	4	1	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: *Daily Predictors*												
(F)-ADL	0.66	0.45	0.56	0.50	0.87	0.28	0.91	0.63	0.76	0.60	0.80	0.55
(F)-ADL-MIDAS ($J_X = 0$)	0.74	0.44	0.68	0.47	0.86	0.43	0.80	0.41	0.77	0.52	0.82	0.57
(F)-ADL-MIDAS ($J_X = 2$)	0.53	0.25	0.53	0.42	0.53	0.37	0.64	0.56	0.51	0.17	0.55	0.15
F-ADL	0.58	0.37	0.51	0.44	0.85	0.65	0.92	0.56	0.78	0.40	0.71	0.46
F-ADL-MIDAS ($J_X = 0$)	0.70	0.42	0.65	0.50	0.83	0.68	0.80	0.34	0.75	0.50	0.74	0.38
F-ADL-MIDAS ($J_X = 2$)	0.61	0.48	0.62	0.49	0.60	0.58	0.76	0.77	0.62	0.57	0.61	0.37
Panel B: *Daily Factors*												
(F)-ADL	0.68	0.40	0.69	0.53	0.86	0.48	0.78	0.62	0.78	0.70	0.80	0.54
(F)-ADL-MIDAS ($J_X = 0$)	0.80	0.47	0.72	0.47	0.84	0.49	0.86	0.51	0.77	0.54	0.88	0.63
(F)-ADL-MIDAS ($J_X = 2$)	0.50	0.45	0.57	0.38	0.55	0.10	0.60	0.45	0.46	0.35	0.54	0.32
F-ADL	0.62	0.32	0.61	0.80	0.79	0.35	0.73	0.56	0.75	0.56	0.72	0.45
F-ADL-MIDAS ($J_X = 0$)	0.78	0.50	0.69	0.26	0.82	0.61	0.86	0.54	0.72	0.55	0.85	0.59
F-ADL-MIDAS ($J_X = 2$)	0.62	0.71	0.71	0.60	0.60	0.16	0.70	0.57	0.51	0.66	0.58	0.17

Table 7: Blockwise Analysis of Forecast Combinations for CPIcore Inflation

Table 7 presents a blockwise analysis of RMSFEs of forecast combinations based on 2DMSFE forecast with $\delta = 0.9$ for CPIcore Inflation relative to the RMSFE of UCSV for 1- and 4-step ahead forecasts. Columns (1)-(2) refer to the results based on all 90 predictors (for the daily predictors) or 988 predictors (for the daily factors). Pairs of Columns (3)-(4), (5)-(6),(7)-(8), (9)-(10), and (11)-(12) refer to subsets of variables based the classes of Commodities, Corporate Risk, Equities, Exchange Rates, and Government Securities, respectively. All models are summarized in Table A3. The notation (F) is used to denote that the forecast combination did not condition on including or excluding the quarterly factors but rather attached weights across ADL and F-ADL models. Entries below one imply improvements compared to the benchmark. The estimation period is 1999:Q1 to 2005:Q4 and the forecasting period is 2006:Q1 + h to 2008:Q4 - h.

	ALL		COMMOD		CORPRSK		EQUIT		FX		GOVSEC	
Forecast Horizon	1	4	1	4	1	4	1	4	1	4	1	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Daily Predictors											
(F)-ADL	0.82	0.45	0.77	0.46	0.93	0.39	0.95	0.58	0.89	0.56	0.86	0.38
(F)-ADL-MIDAS ($J_X = 0$)	0.86	0.37	0.83	0.40	0.94	0.40	0.95	0.52	0.92	0.38	0.86	0.32
(F)-ADL-MIDAS ($J_X = 2$)	0.62	0.30	0.60	0.31	0.69	0.23	0.73	0.52	0.63	0.22	0.65	0.47
F-ADL	0.81	0.24	0.77	0.66	0.93	0.82	0.97	0.62	0.90	0.41	0.81	0.29
F-ADL-MIDAS ($J_X = 0$)	0.83	0.27	0.80	0.21	0.91	0.69	0.95	0.56	0.91	0.36	0.82	0.33
F-ADL-MIDAS ($J_X = 2$)	0.68	0.55	0.65	0.54	0.74	0.71	0.78	0.72	0.69	0.52	0.71	0.52
	Panel B: Daily Factors											
(F)-ADL	0.91	0.58	0.78	0.40	0.96	0.58	0.89	0.48	0.86	0.52	0.91	0.46
(F)-ADL-MIDAS ($J_X = 0$)	0.88	0.53	0.85	0.49	0.94	0.44	0.94	0.43	0.87	0.48	0.95	0.52
(F)-ADL-MIDAS ($J_X = 2$)	0.64	0.42	0.61	0.46	0.67	0.38	0.66	0.52	0.55	0.37	0.64	0.44
F-ADL	0.89	0.73	0.75	0.57	0.94	0.69	0.87	0.83	0.83	0.61	0.87	0.76
F-ADL-MIDAS ($J_X = 0$)	0.84	0.70	0.85	0.69	0.92	0.39	0.92	0.62	0.83	0.48	0.92	0.58
F-ADL-MIDAS ($J_X = 2$)	0.72	0.53	0.67	0.74	0.71	0.32	0.72	0.37	0.57	0.57	0.68	0.59

Table 8: Robustness: Alternative Forecast Combination Methods

Table 8 presents RMSFEs for forecast combinations for GDP growth (Panel A), PCEcore (Panel B), and CPIcore (Panel C) for the Median, Trimmed Mean (at 5%), Discounted MSFE with discount factor $\delta = 0.9$ (DMSFE), Recently Best over the past 4 quarters (RBest), Smoothed BIC or BMA (SBIC), and Smoothed AIC (SAIC). The results are relative to the RMSFE of RW for GDP growth and relative to the RMSFE of UCSV for PCEcore and CPIcore. All models are summarized in Table A3. The Entries below one imply improvements compared to the benchmark. The results on daily predictors refer to the subset of 90 predictors while the results for the daily factors are based on the larger set of 988 variables. The estimation period is 1999:Q1 to 2005:Q4 and the forecasting period is 2006:Q1 + h to 2008:Q4 - h.

Panel A: GDP Growth

	Median		TRMEAN		DMSE		RBest		Best		SBIC		SAIC	
Forecast Horizon	1	4	1	4	1	4	1	4	1	4	1	4	1	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Benchmarks														
AR	0.97	1.03	0.97	1.03	1.01	1.16	1.04	1.60	0.96	1.03	1.03	1.15	1.03	1.15
FAR	0.73	0.96	0.75	1.03	0.74	0.98	0.74	1.14	0.69	0.77	0.75	2.24	0.93	2.42
Daily Predictors														
ADL	0.97	1.04	0.97	1.03	0.97	1.03	0.51	0.52	0.64	0.57	0.93	0.96	0.94	0.94
FADL	0.77	1.00	0.76	0.99	0.74	0.95	0.34	0.12	0.46	0.47	0.94	1.33	0.89	1.40
ADL-MIDAS ($J_X = 0$)	0.95	1.04	0.94	1.03	0.93	1.03	0.39	0.60	0.57	0.42	0.94	0.79	1.05	0.74
FADL-MIDAS ($J_X = 0$)	0.73	1.01	0.72	1.01	0.69	0.91	0.27	0.16	0.46	0.28	1.01	1.72	0.92	1.72
ADL-MIDAS ($J_X = 2$)	0.62	0.57	0.61	0.56	0.60	0.48	0.35	0.04	0.51	0.33	0.69	0.58	0.67	0.57
FADL-MIDAS ($J_X = 2$)	0.53	0.55	0.53	0.54	0.50	0.42	0.30	0.07	0.43	0.29	0.65	0.87	0.61	0.87
Daily Factors														
ADL	0.95	0.94	0.93	0.92	0.92	0.98	0.59	1.13	0.68	0.78	0.82	0.89	0.93	0.88
FADL	0.78	0.91	0.77	0.89	0.75	0.85	0.62	0.60	0.65	0.40	0.79	1.08	0.77	1.18
ADL-MIDAS ($J_X = 0$)	0.93	0.95	0.92	0.94	0.91	1.02	0.57	1.22	0.66	0.80	0.87	0.97	0.94	0.97
FADL-MIDAS ($J_X = 0$)	0.74	0.95	0.73	0.95	0.70	0.98	0.44	1.02	0.60	0.68	0.90	1.46	0.82	1.46
ADL-MIDAS ($J_X = 2$)	0.59	0.39	0.58	0.40	0.53	0.37	0.33	0.34	0.47	0.47	0.55	0.58	0.71	0.58
FADL-MIDAS ($J_X = 2$)	0.54	0.47	0.53	0.44	0.49	0.38	0.36	0.40	0.47	0.56	0.74	1.00	0.76	1.00

Table 8 continued

Panel B: PCEcore Inflation

	Median		TRMEAN		DMSE		RBest		Best		SBIC		SAIC	
Forecast Horizon	1	4	1	4	1	4	1	4	1	4	1	4	1	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Benchmarks														
AR	1.05	0.78	1.05	0.78	0.98	0.86	1.04	1.14	0.98	0.74	1.02	0.83	1.01	0.83
FAR	0.96	0.80	0.98	0.93	0.94	0.79	1.01	1.07	0.90	0.78	1.52	0.77	1.55	0.76
Daily Predictors														
ADL	1.01	1.02	0.98	1.01	0.90	0.83	0.32	0.46	0.66	0.54	0.95	1.13	0.93	1.26
FADL	1.00	1.25	0.98	1.19	0.79	0.70	0.27	0.16	0.35	0.42	1.19	0.88	1.07	1.32
ADL-MIDAS ($J_X = 0$)	0.99	0.81	0.99	0.87	0.92	0.74	0.32	0.04	0.63	0.30	1.05	1.84	1.33	1.83
FADL-MIDAS ($J_X = 0$)	0.95	0.97	0.96	1.08	0.82	0.67	0.23	0.16	0.49	0.29	1.23	0.98	1.33	0.98
ADL-MIDAS ($J_X = 2$)	0.70	0.63	0.72	0.69	0.59	0.44	0.34	0.33	0.54	0.26	1.57	1.18	1.55	1.22
FADL-MIDAS ($J_X = 2$)	0.84	1.28	0.86	1.31	0.71	0.84	0.32	0.50	0.59	0.34	1.15	0.97	1.01	0.97
Daily Factors														
ADL	1.04	1.02	1.02	1.01	0.89	0.74	0.40	0.50	0.70	0.51	1.22	0.63	1.18	0.63
FADL	1.00	1.29	1.00	1.25	0.80	0.60	0.45	0.38	0.58	0.27	0.80	0.95	0.71	0.97
ADL-MIDAS ($J_X = 0$)	0.99	0.84	1.00	0.87	0.94	0.73	0.40	0.41	0.74	0.50	0.98	0.67	1.03	0.67
FADL-MIDAS ($J_X = 0$)	0.98	0.94	0.97	1.06	0.86	0.69	0.54	0.50	0.67	0.34	1.11	2.04	0.87	2.02
ADL-MIDAS ($J_X = 2$)	0.69	0.73	0.69	0.75	0.57	0.58	0.41	0.42	0.67	0.30	0.53	1.06	0.53	1.06
FADL-MIDAS ($J_X = 2$)	0.84	1.22	0.86	1.37	0.70	0.97	0.50	0.70	0.76	0.60	0.56	2.96	0.56	2.99

Table 8 continued

Panel C: CPIcore Inflation

	Median		TRMEAN		DMSE		RBest		Best		SBIC		SAIC	
Forecast Horizon	1	4	1	4	1	4	1	4	1	4	1	4	1	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Benchmarks														
AR	1.09	0.68	1.09	0.68	1.00	0.76	0.98	1.00	1.02	0.68	1.00	0.85	1.00	0.80
FAR	1.02	0.94	1.02	0.87	0.94	0.50	0.88	0.64	0.94	0.87	1.06	0.44	1.14	1.30
Daily Predictors														
ADL	1.01	0.74	1.01	0.71	0.93	0.66	0.35	0.51	0.62	0.44	1.09	0.78	1.28	0.83
FADL	0.95	0.91	0.95	0.93	0.87	0.58	0.36	0.34	0.71	0.41	1.51	0.62	1.57	0.69
ADL-MIDAS ($J_X = 0$)	1.05	0.69	1.05	0.68	0.96	0.57	0.51	0.24	0.69	0.39	1.11	0.95	1.46	0.92
FADL-MIDAS ($J_X = 0$)	0.98	0.93	0.99	0.93	0.90	0.52	0.23	0.15	0.67	0.32	1.41	2.91	1.60	2.89
ADL-MIDAS ($J_X = 2$)	0.79	0.57	0.81	0.61	0.66	0.46	0.21	0.26	0.73	0.21	1.22	0.94	1.24	0.95
FADL-MIDAS ($J_X = 2$)	0.86	1.04	0.86	1.04	0.74	0.71	0.37	0.55	0.78	0.43	1.03	1.13	1.12	1.15
Daily Factors														
ADL	1.05	0.66	1.05	0.65	0.99	0.63	0.59	0.69	0.86	0.55	0.97	0.44	1.01	0.26
FADL	0.96	0.86	0.98	0.83	0.92	0.76	0.52	0.84	0.81	0.65	0.97	2.12	0.96	2.07
ADL-MIDAS ($J_X = 0$)	1.06	0.69	1.07	0.67	0.99	0.58	0.58	0.74	0.87	0.48	1.00	0.31	0.91	0.73
FADL-MIDAS ($J_X = 0$)	0.98	0.98	1.00	0.98	0.91	0.69	0.69	0.98	0.84	0.71	1.00	2.07	0.93	1.93
ADL-MIDAS ($J_X = 2$)	0.80	0.69	0.81	0.67	0.66	0.47	0.35	0.61	0.81	0.40	0.87	1.53	0.82	1.44
FADL-MIDAS ($J_X = 2$)	0.85	1.10	0.86	0.97	0.74	0.70	0.43	0.21	0.75	0.82	0.88	1.98	0.97	1.95

Table 9: Robustness: Mean Forecast Analysis for the Various Classes of Assets

Table 9 presents a blockwise analysis of RMSFEs of forecast combinations based on the Mean forecast for 1- and 4-step ahead forecasts. The results for GDP Growth (Panel A) are relative to the RMSFE of RW while the results for PCEcore Inflation (Panel B) and CPIcore Inflation (Panel C) are relative to the RMSFE of UCSV, respectively. Columns (1)-(2) refer to the results based on all 90 predictors (for the daily predictors) or 988 predictors (for the daily factors). Pairs of Columns (3)-(4), (5)-(6),(7)-(8), (9)-(10), and (11)-(12) refer to subsets of variables based the classes of Commodities, Corporate Risk, Equities, Exchange Rates, and Government Securities, respectively. All models are summarized in Table A3. The notation (F) is used to denote that the forecast combination did not condition on including or excluding the quarterly factors but rather attached weights across ADL and F-ADL models. Entries below one imply improvements compared to the benchmark. The estimation period is 1999:Q1 to 2005:Q4 and the forecasting period is 2006:Q1 + h to 2008:Q4 - h.

	ALL		COMMOD		CORPRSK		EQUIT		FX		GOVSEC	
Forecast Horizon	1	4	1	4	1	4	1	4	1	4	1	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: *GDP Growth*												
Daily Predictors												
(F)-ADL	0.85	1.00	0.88	1.05	0.81	0.86	0.84	1.01	0.83	1.21	0.88	0.91
(F)-ADL-MIDAS ($J_X = 0$)	0.83	1.00	0.85	1.03	0.79	0.88	0.83	1.05	0.83	1.23	0.85	0.95
(F)-ADL-MIDAS ($J_X = 2$)	0.55	0.54	0.57	0.61	0.54	0.42	0.51	0.47	0.57	0.64	0.55	0.50
Daily Factors												
(F)-ADL	0.84	0.89	0.88	1.03	0.79	0.84	0.90	0.94	0.79	0.96	0.90	0.97
(F)-ADL-MIDAS ($J_X = 0$)	0.81	0.94	0.85	1.07	0.79	0.92	0.87	0.99	0.79	1.02	0.83	1.01
(F)-ADL-MIDAS ($J_X = 2$)	0.53	0.41	0.57	0.57	0.55	0.46	0.59	0.52	0.57	0.49	0.56	0.59
Panel B: *PCEcore Inflation*												
Daily Predictors												
(F)-ADL	0.95	0.99	0.89	0.98	1.07	1.04	1.00	0.96	0.91	1.16	1.02	1.14
(F)-ADL-MIDAS ($J_X = 0$)	0.95	0.86	0.92	0.87	1.01	0.88	0.91	0.80	0.92	0.93	0.99	0.96
(F)-ADL-MIDAS ($J_X = 2$)	0.75	0.90	0.75	0.93	0.75	0.82	0.80	0.98	0.75	0.73	0.78	1.05
Daily Factors												
(F)-ADL	0.99	1.07	0.91	1.01	1.07	1.08	1.00	1.00	1.01	1.17	1.06	1.11
(F)-ADL-MIDAS ($J_X = 0$)	0.96	0.91	0.94	0.86	0.98	0.90	0.98	0.87	0.98	0.97	1.01	0.94
(F)-ADL-MIDAS ($J_X = 2$)	0.74	0.93	0.75	0.98	0.74	0.68	0.76	0.87	0.71	0.86	0.74	0.80
Panel C: *CPIcore Inflation*												
Daily Predictors												
(F)-ADL	0.98	0.77	0.94	0.77	1.05	0.82	1.01	1.22	0.95	0.69	1.00	0.75
(F)-ADL-MIDAS ($J_X = 0$)	1.02	0.73	1.00	0.71	1.07	0.82	1.03	1.15	1.01	0.62	1.02	0.74
(F)-ADL-MIDAS ($J_X = 2$)	0.84	0.80	0.83	0.79	0.86	0.85	0.87	1.14	0.82	0.76	0.83	0.86
Daily Factors												
(F)-ADL	1.02	0.72	0.98	0.66	1.07	0.98	1.00	0.98	1.01	0.66	1.02	0.89
(F)-ADL-MIDAS ($J_X = 0$)	1.04	0.80	1.02	0.75	1.07	1.14	1.05	1.08	1.02	0.70	1.07	1.00
(F)-ADL-MIDAS ($J_X = 2$)	0.83	0.81	0.83	0.84	0.85	1.23	0.83	1.31	0.79	0.61	0.83	1.02

Table 10: Testing

This table presents statistics for forecast evaluation of the predictive gains between of FADL-MIDAS ($J_X = 2$) over FADL models. The Theil's U statistic is the ratio of the means of RMSFEs of FADL-MIDAS ($J_X = 2$) models over the 90 predictors over the corresponding mean of FADL models. The bootstrap p-value is based on 2000 bootstrap resamples from the empirical distribution of the asset based distribution of the DM statistics. The Panel Sum-Difference test is based on the auxiliary panel regression of the sum of the squared forecast errors between FADL-MIDAS and FADL on the corresponding difference.

	GDP Growth		CPI core	
Forecast Horizon	1	4	1	4
FADL-MIDAS ($J_X = 2$) *vs. FADL*				
Panel Theil's U	0.677	0.468	0.812	0.935
Mean Panel DM statistics	−0.514	−0.349	−0.116	−0.083
Bootstrap p-value - Panel DM stat	0.000	0.002	0.000	0.048
Panel Sum-Difference test				
with fixed effects	0.000	0.008	0.000	0.055
with fixed and time effects	0.000	0.034	0.000	0.176

References

Aiolfi, Marco, and Allan Timmermann, 2006, Persistence in Forecasting Performance and Conditional Combination Strategies, *Journal of Econometrics* 135, 31–53.

Alper, C. Erme, Salih Fendoglu, and Burak Saltoglu, 2008, Forecasting Stock Market Volatilities Using MIDAS Regressions: An Application to the Emerging Markets, MPRA Paper No. 7460.

Andreou, Elena, Eric Ghysels, and Andros Kourtellos, 2010, Regression Models With Mixed Sampling Frequencies, *Journal of Econometrics*, in-press.

Ang, Andrew, Geert Bekaert, and Ming Wei, 2007, Do Macro Variables, Asset Markets, or Surveys Forecast Inflation Better?, *Journal of Monetary Economics* 54, 1163–1212.

Ang, Andrew, Monika Piazzesi, and Ming Wei, 2006, What Does the Yield Curve Tell us about GDP Growth?, *Journal of Econometrics* 131, 359–403.

Angelini, Elena, Gonzalo Camba-Mendez, Domenico Giannone, Gerhard Rünstler, and Lucrezia Reichlin, 2008, A Two-Step Estimator for Large Approximate Dynamic Factor Models Based on Kalman Filtering, ECB Working Papers.

Armesto, Michelle T., Rubén Hernandez-Murillo, Michael Owyang, and Jeremy Piger, 2009, Measuring the Information Content of the Beige Book: A Mixed Data Sampling Approach, *Journal of Money, Credit and Banking* 41, 35–55.

Aruoba, S. Boragan, Frank X. Diebold, and Chiara Scotti, 2009, Real-time measurement of business conditions, *Journal of Business and Economic Statistics* 27, 417–427.

Atkeson, Andrew, and Lee E. Ohanian, 2001, Are Phillips curves useful for forecasting inflation?, *Federal Reserve Bank of Minneapolis Quarterly Review* 25, 2–11.

Avramov, Doron, 2002, Stock Return Predictability and Model Uncertainty, *Journal of Financial Economics* 64, 423–458.

Bai, Jushan, 2003, Inferential theory for factor models of large dimensions, *Econometrica* pp. 135–171.

Bai, Jennie, Eric Ghysels, and Jonathan Wright, 2009, State space models and MIDAS regressions, Working paper, NY Fed, UNC and Johns Hopkins.

Bai, Jushan, and Serena Ng, 2002, Determining the number of factors in approximate factor models, *Econometrica* 70, 191–221.

———, 2005, The Power of Tests of Predictive Ability in the Presence of Structural Breaks, *Journal of Econometrics* 124, 1–31.

Barro, Robert J., 1990, The Stock Market and Investment, *Review of Financial Studies* 3, 115–131.

Bates, John, and Clive W.J. Granger, 1969, The combination of forecasts, *Operations Research* pp. 451–468.

Bernanke, Ben, 1983, Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression, *American Economic Review* 73, 257–276.

———, 1990, On the Predictive Power of Interest Rates and Interest Rate Spreads, *New England Economic Review* pp. 51–68.

———, Mark Gertler, and Mark Watson, 1997, Systematic monetary policy and the effects of oil price shocks, *Brookings Papers on Economic Activity* 1, 91–157.

Bernanke, Ben S., and Allan S. Blinder, 1992, The Federal Funds Rate and the Channels of Monetary Transmission, *American Economic Review* 82, 901–921.

Burnham, Kenneth P., and David R. Anderson, 2002, *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach* (Springer).

Chen, Xilong, and Eric Ghysels, 2009, News - good or bad - and its impact on predicting future volatility, *Review of Financial Studies* (forthcoming).

Chen, Yu-Chin, Kenneth Rogoff, and Barbara Rossi, 2010, Can Exchange Rates Forecast Commodity Prices?, *Quarterly Journal of Economics*, forthcoming.

Clements, Michael P., and Ana B. Galvão, 2008, Macroeconomic Forecasting with Mixed Frequency Data: Forecasting US output growth, *Journal of Business and Economic Statistics* 26, 546–554.

———, 2009, Forecasting US output growth using Leading Indicators: An appraisal using MIDAS models, *Journal of Applied Econometrics* 24, 1187–1206.

D'Agostino, Antonello, Paolo Surico, and Domenico Giannone, 2009, Macroeconomic Forecasting and Structural Change, Working Paper Series 605, European Central Bank.

Diebold, Frank X., and Roberto S. Mariano, 1995, Comparing Predictive Accuracy, *Journal of Business and Economic Statistics* 13, 253–265.

Doz, Catherine, Domenico Giannone, and Lucrezia Reichlin, 2006, A Two-Step Estimator for Large Approximate Dynamic Factor Models Based on Kalman Filtering, CEPR Discussion Papers 6043.

——— , 2008, A Quasi Maximum Likelihood Approach for Large Approximate Dynamic Factor Models, CEPR Discussion Papers 5724.

Edelstein, Paul, 2009, Commodity Prices, Inflation Forecasts, and Monetary Policy, Working Paper, University of Michigan.

Engel, Charles, and Kenneth D. West, 2005, Exchange Rates and Fundamentals , *The Journal of Political Economy* 113, 485–517.

Engle, Robert F., Eric Ghysels, and Bumjean Sohn, 2008, On the Economic Sources of Stock Market Volatility, Discussion Paper NYU and UNC.

Estrella, Arturo, and Gikas A. Hardouvelis, 1991, The Term Structure as a Predictor of Real Economic Activity, *Journal of Finance* 46, 555–576.

Fama, Eugene, 1990, Term-structure forecasts of interest rates, inflation, and real returns, *Journal of Monetary Economics* 25, 59–76.

Fischer, Stanley, and Robert C. Merton, 1984, Macroeconomics and Finance: The Role of the Stock Market, *Carnegie-Rochester Conference Series on Public Policy* 21, 57–108.

Forni, Mario, Marc Hallin, Marco Lippi, and Lucrezia Reichlin, 2000, The generalized dynamic-factor model: Identification and estimation, *Review of Economics and Statistics* 82, 540–554.

——— , 2003, Do financial variables help forecasting inflation and real activity in the euro area?, *Journal of Monetary Economics* 50, 1243–1255.

——— , 2005, The generalized dynamic factor model, *Journal of the American Statistical Association* 100, 830–840.

Forsberg, Lars, and Eric Ghysels, 2006, Why do absolute returns predict volatility so well?, *Journal of Financial Econometrics* 6, 31–67.

Friedman, Benjamin M., and Kenneth N. Kuttner, 1992, Money, Income, Prices and Interest Rates, *American Economic Review* 82, 472–492.

Galvão, Ana B., 2006, Changes in Predictive Ability with Mixed Frequency Data, Discussion Paper QUeen Mary.

Ghysels, Eric, Pedro Santa-Clara, and Ross Valkanov, 2004, The midas touch: Mixed data sampling regressions, Discussion paper UNC and UCLA.

——— , 2005, There is a risk-return tradeoff after all, *Journal of Financial Economics* 76, 509–548.

Ghysels, Eric, Pedro Santa-Clara, and Rossen Valkanov, 2006, Predicting volatility: getting the most out of return data sampled at different frequencies, *Journal of Econometrics* 131, 59–95.

Ghysels, Eric, Arthur Sinko, and Ross Valkanov, 2006, MIDAS regressions: Further results and new directions, *Econometric Reviews* 26, 53–90.

Ghysels, Eric, and Jonathan Wright, 2009, Forecasting professional forecasters, *Journal of Business and Economic Statistics* 27, 504–516.

Giannone, Domenico, Lucrezia Reichlin, and David Small, 2008, Nowcasting: The real-time informational content of macroeconomic data, *Journal of Monetary Economics* 55, 665–676.

Gordon, Robert J., 1982, Inflation, Flexible Exchange Rates, and the Natural Rate of Unemployment, *Workers, Jobs, and Inflation, Brookings Institution.*

——— , 1998, Foundations of the Goldilocks Economy: Supply Shocks and the Time-Varying NAIRU, *Brookings Papers of Economic Activity* 1, 297–333.

Granger, Clive W.J., and Ling-ling Huang, 1997, Evaluation of panel data models: Some suggestions from times series, UCSD working paper.

Gurkaynak, Refet S., Brian Sack, and Jonathan Wright, 2010, The TIPS yield curve and In.ation Compensation, *American Economics Journal: Macroeconomics* 2, 70–92.

Hamilton, James D., 2006, Daily Monetary Policy Shocks and the Delayed Response of New Home Sales, working paper, UCSD.

——— , and Dong H. Kim, 2002, A Re-Examination of the Predictability of Economic Activity using the Yield Spread, *Journal Money, Credit and Banking* 34, 340–360.

Hansen, Bruce, 2007, Least Squares Model Averaging, *Econometrica* 75, 1175–1189.

——— , 2008, Least Squares Forecast Averaging, *Journal of Econometrics* 146, 342–350.

Harvey, Andrew, 1989a, *Forecasting, Structural Time Series Models and the Kalman Filter* (Cambridge University Press, Cambridge).

Harvey, Andrew C., and Richard G. Pierse, 1984, Estimating missing observations in economic time series, *Journal of the American Statistical Association* 79, 125–131.

Harvey, Campbell R, 1988, The Real Term Structure and Consumption Growth, *Journal of Financial Economics* 22, 305–333.

——— , 1989b, Forecasts of Economic Growth from the Bond and Stock Markets, *Financial Analysts Journal* 45, 38–45.

Kuzin, Vladimir, Massimiliano Marcellino, and Christian Schumacher, 2009, MIDAS versus mixed-frequency VAR: nowcasting GDP in the euro area, Discussion Paper 07/2009 Deutsche Bundesbank.

Laurent, Robert D., 1988, An Interest Rate-Based Indicator of Monetary Policy, *Federal Reserve Bank Chicago Economic Perspectives* 12, 3–14.

——— , 1989, Testing the Spread, *Federal Reserve Bank Chicago Economic Perspectives* 13, 22–34.

León, Ángel., Juan M. Nave, and Gonzalo Rubio, 2007, The relationship between risk and expected return in Europe, *Journal of Banking and Finance* 31, 495–512.

Ludvigson, Sydney, and Serena Ng, 2007, The Empirical Risk-Return Relation: A Factor Analysis Approach, *The Journal of Financial Economics* 83, 171–222.

——— , 2009, Macro Factors in Bond Risk Premia, *The Review of Financial Studies* 12, 5027–5067.

Mariano, Roberto S., and Yasutomo Murasawa, 2003, A new coincident index of business cycles based on monthly and quarterly series, *Journal of Applied Econometrics* 18, 427–443.

Mishkin, Frederic S., 1990a, The Information in the Longer-Maturity Term Structure About Future Inflation, , *Quarterly Journal of Economics* 55, 815–28.

———, 1990b, What Does the Term Structure Tell Us About Future Inflation?, *Journal of Monetary Economics* 25, 77–95.

Mitchell, Wesley C., and Arthur F. Burns, 1938, *Statistical Indicators of Cyclical Revivals* (Princeton U. Press: Princeton).

Mittnik, Stefan, and Peter A. Zadrozny, 2004, *Forecasting quarterly German GDP at monthly intervals using monthly Ifo business conditions data* (Springer).

Moench, Emanuel, Serena Ng, and Simon Potter, 2009, Dynamic hierarchical factor models, Staff Reports 412, Federal Reserve Bank of New York.

Rossi, Barbara, and Tatevik Sekhposyan, 2010, Has Models' Forecasting Performance Changed Over Time, and When? , International Journal of Forecasting, forthcoming.

Schumacher, Christian, and Jorg Breitung, 2008, Real-time forecasting of German GDP based on a large factor model with monthly and quarterly data, *International Journal of Forecasting* 24, 386–398.

Sims, Christopher A., 1980, A Comparison of Interwar and Postwar Cycles: Monetarism Reconsidered, *American Economic Review* 70, 250–257.

Stock, James H., and Mark W. Watson, 1989, New indexes of coincident and leading economic indicators, *NBER Macroeconomics Annual* pp. 351–394.

———, 2002a, Forecasting using principal components from a large number of predictors, *Journal of the American Statistical Association* 97, 1167–1179.

———, 2002b, Macroeconomic forecasting using diffusion indexes, *Journal of Business and Economic Statistics* 20, 147–162.

———, 2003, Forecasting output and inflation: the role of asset prices, *Journal of Economic Literature* pp. 788–829.

———, 2004, Combination Forecasts Of Output Growth In A Seven-Country Data Set, *Journal of Forecasting* 23, 405–430.

———, 2006, Macroeconomic forecasting using many predictors, in Allan Timmerman Graham Elliott, Clive Granger, ed.: *Handbook of Economic Forecasting* . pp. 87–115 (North Holland: Amsterdam).

———, 2007, Why has US inflation become harder to forecast?, *Journal of Money, Credit and Banking* 39, 3–33.

———, 2008a, Forecasting in Dynamic Factor Models Subject to Structural Instability, in Jennifer Castle, and Neil Shephard, ed.: *The Methodology and Practice of Econometrics, A Festschrift in Honour of Professor David F. Hendry*. Oxford University Press.

———, 2008b, Phillips Curve Inflation Forecasts, NBER Working paper.

Tay, Anthony, 2006, Financial Variables as Predictors of Real Output Growth, Discussion Paper SMU.

Tay, Anthony S., 2007, Mixing Frequencies: Stock Returns as a Predictor of Real Output Growth, Discussion Paper SMU.

Timmermann, Allan, 2006, Forecast combinations, in Allan Timmerman Graham Elliott, Clive Granger, ed.: *Handbook of Economic Forecasting*vol. 1 . pp. 136–196 (North Holland: Amsterdam).

Van Dijk, Dick, and Marianne Sensier, 2004, Testing for volatility changes in us macroeconomic time series, *Review of Economics and Statistics* 86, 833–839.

Wright, Jonathan, 2008, Bayesian Model Averaging and Exchange Rate Forecasting, *Journal of Econometrics* 146, 329–341.

Zadrozny, Peter A., 1990, Forecasting US GNP at monthly intervals with an estimated bivariate time series model, *Federal Reserve Bank of Atlanta Economic Review* 75, 2–15.

Table A1: Daily Data Series

Index	Short Name	Trans Code	Definition
			Commodities
1	RJ CRB	5	Reuters/Jefferies Crb Futures Price Index: All Commodities (1967̄100)
2	Brent Oil	5	Europe Brent Spot Price FOB (Dollars Per Barrel)
3	Silver	5	S&P Gsci Silver Index (Dec-29-72=100)
4	PL-NYD	5	Platinum Cash Price (US$/Ounce)
5	Zinc	5	S&P Gsci Zinc Index (Dec-31=90=100)
6	XPD-D	5	Palladium (USD per Troy Ounce)
7	Wheat	5	S&P Gsci Wheat Index (Dec-31-69=100)
8	C-US2D	5	Corn Spot Price (US$/Bushel)
9	Soyb	5	S&P Gsci Soybeans Index (Dec-31-69=100)
10	Cotton	5	S&P Gsci Cotton Index
11	Sugar	5	S&P Gsci Sugar Index (Dec-29-72=100)
12	Coffee	5	S&P Gsci Coffee Index (Dec-31-80=100)
13	Cocoa	5	S&P Gsci Cocoa Index (Dec-30-83=100)
14	BO1599D	5	Soybean Oil Cash Price (Cents/Pound)
15	OATS-D	5	Oat Spot Price (US$/Bushel)
16	Cattle	5	S&P Gsci Live Cattle Index (Dec-31-69=100)
17	Hogs	5	S&P Gsci Lean Hogs Index (Dec-31-75=100)
18	Gold	5	S&P Gsci Gold Index
19	Aluminum	5	S&P Gsci Aluminum Index (Dec-31-90=100)
20	WTI Oil	5	Commodity Prices: Crude Oil, West Texas Intermediate ($/Barrel)
21	Lead	5	S&P Gsci Lead Index (Dec-30-94=100)
22	Nickel	5	S&P Gsci Nickel Index (Dec-31-92=100)
23	Tin	5	LME Tin: Closing Cash Price ($/Metric Tonne)
24	WC1-ID	5	CBOT Wheat Futures Prices
25	CC1-ID	5	CBOT Corn Futures Prices
26	SC1-ID	5	CBOT Soybean Futures Prices
27	CTC1-D	5	Cotton Futures Prices
28	Sugar-Fut	5	World Sugar Futures Price: 1St Expiring Contract Settlement (Cents/Lb)
29	KCC1-D	5	CSCE Coffee Futures Prices
30	CCC1-D	5	CSCE Cocoa Futures Prices (USD/Metric Ton)
31	BOC1-D	5	Soybean Oil Futures Price (Cents/Pound)
32	OC1-ID	5	Oat Futures Price
33	LCC1-D	5	Live Cattle Futures
34	LHC1-D	5	Live Hog Futures
35	GCC1-D	5	COMEX Gold Futures Prices
36	Alum Fut	5	Lme Aluminum, 99.7% Purity: Closing 3-Month Forward Price ($Metric/Tonne)
37	WTI Oil Fut	5	Light Sweet Crude Oil Futures Price: 1St Expiring Contract Settlement ($/Bbl)
38	Lead Fwd	5	Lme Lead: Closing 3-Month Forward Price ($/Metric Tonne)
39	Nickel Fwd	5	Lme Nickel: Closing 3-Month Forward Price ($/Metric Tonne)
40	Tin Fwd	5	Lme Tin: Closing 3-Month Forward Price ($/Metric Tonne)

Table continued on next page ...

Table A1 continued

Index	Short Name	Trans Code	Definition
			Corporate Risk
1	LIBOR	2	Overnight London Interbank Offered Rate (%)
2	1MLIBOR	2	1-Month London Interbank Offered Rate (%)
3	3MLIBOR	2	3-Month London Interbank Offered Rate (%)
4	6MLIBOR	2	6-Month London Interbank Offered Rate (%)
5	1YLIBOR	2	One-Year London Interbank Offered Rate (%)
6	1MEuro-FF	1	1-Month Eurodollar Deposits (London Bid) (% P.A.) *minus* Fed Funds
7	3MEuro-FF	1	3-Month Eurodollar Deposits (London Bid) (% P.A.) *minus* Fed Funds
8	6MEuro-FF	1	6-Month Eurodollar Deposits (London Bid) (% P.A.) *minus* Fed Funds
9	APFNF-AANF	1	1-Month A2/P2/F2 Nonfinancial Commercial Paper (% Per Annum) *minus* 1-Month Aa Nonfinancial Commercial Paper (% Per Annum)
10	APFNF-AAF	1	1-Month A2/P2/F2 Nonfinancial Commercial Paper (% Per Annum) *minus* 1-Month Aa Financial Commercial Paper (% Per Annum)
11	TED	1	3Month Tbill *minus* 3-Month London Interbank Offered Rate (%)
12	MAaa-10YTB	1	Moody'S Seasoned Aaa Corporate Bond Yield (% P.A.) *minus* Y10-Tbond
13	MBaa-10YTB	1	Moody'S Seasoned Baa Corporate Bond Yield (% P.A.) *minus* Y10-Tbond
14	MLA-10YTB	1	Merrill Lynch Corporate Bonds: A Rated: Effective Yield (%) *minus* Y10-Tbond
15	MLAA-10YTB	1	Merrill Lynch Corporate Bonds: Aa Rated: Effective Yield (%) *minus* Y10-Tbond
16	MLAAA-10YTB	1	Merrill Lynch Corporate Bonds: Aaa Rated: Effective Yield (%) *minus* Y10-Tbond
			Equity
1	S&P500	5	Standard & Poor's 500 Stock price index (1941-43=10)
2	S&P500 Fut	5	S&P 500 Futures price: 1st expiring contract settlement (Index)
3	SPI	5	Standard & Poor's 500 Industrial stock price index (1941-43=100)
4	DJI	5	Stock price averages: Dow Jones 30 Industrials, NYSE (close)
5	DJI Fut	5	Dow Jones Industrials Futures Contract
6	Nasdaq	5	Stock price index:Nasdaq Composite (2/5/71=100)
7	Nasdaq100	5	Stock price index:Nasdaq 100
8	VIX	1	CBOE market volatility index, VIX
9	MKT-RF	1	MKT *minus* RF
10	S&P500toVIX	5	S&P500/VIX

Table continued on next page ...

Table A1 continued

Index	Short Name	Trans Code	Definition
			Foreign Exchange Rate
1	EFXbroad	5	Effective exchange rate-broad
2	EFXmajor	5	Effective exchange rate-major
3	Canadian$/US$	5	Canada: spot exchange middle rate, NY close (Canadian$/US$)
4	Euro/US$	5	Europe: spot exchange middle rate, NY close (Euro/US$)
5	Japanese Yen/US$	5	Japan: spot exchange middle rate, NY close (Yen/US$)
6	Swiss Franc/US$	5	Switzerland: spot exchange middle rate, NY close (Francs/US$)
7	UK/US$	5	United Kingdom: spot exchange middle rate, NY close (Pounds/US$)
			Government Securities
1	FF	2	Federal Funds [Effective] rate (% P.A.)
2	3MTB	2	3-month treasury bills, secondary market (% P.A.)
3	6MTB	2	6-month treasury bills, secondary market (% P.A.)
4	1YTB	2	1-year treasury bill yield at constant maturity (% P.A.)
5	10YTB	2	10-year treasury bond yield at constant maturity (% P.A.)
6	BEIR5	1	US Inflation compensation: continuously compounded zero-coupon yield: 5-year (%)
7	BEIR10	1	US Inflation compensation: continuously compounded zero-coupon yield: 10-year (%)
8	BEIR1F4	1	BKEVEN1F4
9	BEIR1F9	1	BKEVEN1F9
10	BEIR5-10	1	US Inflation compensation: coupon equivalent forward rate: 5-10 years (%)
11	6MTB-FF	1	6-month treasury bill market bid yield at constant maturity (%) *minus* Fed Funds
12	1YTB-FF	1	1-year treasury bill yield at constant maturity (% P.A.) *minus* Fed Funds
13	10YTB-FF	1	10-year treasury bond yield at constant maturity (% P.A.) *minus* Fed Funds
14	6MTB-3MTB	1	6-month treasury bill yield at constant maturity (% P.A.) *minus* M3-Tbills
15	1YTB-3MTB	1	1-year treasury bill yield at constant maturity (% P.A.) *minus* M3-Tbills
16	10YTB-3MTB	1	10-year treasury bond yield at constant maturity (% P.A.) *minus* M3-Tbills
			Coincident Indicator
1	ADS	1	Daily Aruoba-Diebold-Scotti Business Conditions Index

Table A2: Quarterly Data Series

Code	Long Description	Short Desc	TCode	Scale
GDP253	Real Personal Consumption Expenditures - Durable Goods , Quantity Index (2000=	Cons-Dur	5	400
GDP254	Real Personal Consumption Expenditures - Nondurable Goods, Quantity Index (200	Cons-NonDur	5	400
GDP255	Real Personal Consumption Expenditures - Services, Quantity Index (2000=100) ,	Cons-Serv	5	400
GDP259	Real Gross Private Domestic Investment - Nonresidential - Structures, Quantity	NonResInv-Struct	5	400
GDP260	Real Gross Private Domestic Investment - Nonresidential - Equipment & Software	NonResInv-Bequip	5	400
GDP261	Real Gross Private Domestic Investment - Residential, Quantity Index (2000=100	Res.Inv	5	400
GDP263	Real Exports, Quantity Index (2000=100) , SAAR	Exports	5	400
GDP264	Real Imports, Quantity Index (2000=100) , SAAR	Imports	5	400
GDP266	Real Government Consumption Expenditures & Gross Investment - Federal, Quantit	Gov Fed	5	400
GDP267	Real Government Consumption Expenditures & Gross Investment - State & Local, Q	Gov State/Loc	5	400
LBOUT	OUTPUT PER HOUR ALL PERSONS: BUSINESS SEC(1982=100,SA)	Labor Prod	5	400
LBPUR7	REAL COMPENSATION PER HOUR,EMPLOYEES:NONFARM BUSINESS(82=100,SA)	Real Comp/Hour	5	400
LBMNU	HOURS OF ALL PERSONS: NONFARM BUSINESS SEC (1982=100,SA)	Emp. Hours	5	400
LBLCPU	UNIT LABOR COST: NONFARM BUSINESS SEC (1982=100,SA)	Unit Labor Cost	5	400
GDP274_1	Motor vehicles and parts Price Index	PCED-DUR-MOTORVEH	6	400
GDP274_2	Furniture and household equipment Price Index	PCED-DUR-HHEQUIP	6	400
GDP274_3	Other Price Index	PCED-DUR-OTH	6	400
GDP275_1	Food Price Index	PCED-NDUR-FOOD	6	400
GDP275_2	Clothing and shoes Price Index	PCED-NDUR-CLTH	6	400
GDP275_3	Gasoline, fuel oil, and other energy goods Price Index	PCED-NDUR-ENERGY	6	400
GDP275_4	Other Price Index	PCED-NDUR-OTH	6	400
GDP276_1	Housing Price Index	PCED-SERV-HOUS	6	400
GDP276_3	Electricity and gas Price Index	PCED-SERV-H0-ELGAS	6	400
GDP276_4	Other household operation Price Index	PCED-SERV-HO-OTH	6	400
GDP276_5	Transportation Price Index	PCED-SERV-TRAN	6	400
GDP276_6	Medical care Price Index	PCED-SERV-MED	6	400
GDP276_7	Recreation Price Index	PCED-SERV-REC	6	400
GDP276_8	Other Price Index	PCED-SERV-OTH	6	400
GDP280A	Structures	PFI-NRES-STR Price Index	6	400
GDP281A	Equipment and software Price Index	PFI-NRES-EQP	6	400
GDP282A	Residential Price Index	PFI-RES	6	400
GDP284A	Exports Price Index	PEXP	6	400
GDP285A	Imports Price Index	PIMP	6	400
GDP287A	Federal Price Index	PGOV-FED	6	400
GDP288A	State and local Price Index	PGOV-SL	6	400

Table continued on next page ...

Table A2 continued

Code	Long Description	Short Desc	TCode	Scale
IPS13	INDUSTRIAL PRODUCTION INDEX - DURABLE CONSUMER GOODS	IP: cons dble	5	400
IPS18	INDUSTRIAL PRODUCTION INDEX - NONDURABLE CONSUMER GOODS	iIP:cons nondble	5	400
IPS25	INDUSTRIAL PRODUCTION INDEX - BUSINESS EQUIPMENT	IP:bus eqpt	5	400
IPS34	INDUSTRIAL PRODUCTION INDEX - DURABLE GOODS MATERIALS	IP: dble mats	5	400
IPS38	INDUSTRIAL PRODUCTION INDEX - NONDURABLE GOODS MATERIALS	IP:nondble mats	5	400
IPS43	INDUSTRIAL PRODUCTION INDEX - MANUFACTURING (SIC)	IP: mfg	5	400
IPS306	INDUSTRIAL PRODUCTION INDEX - FUELS	IP: fuels	5	400
PMP	NAPM PRODUCTION INDEX (PERCENT)	NAPM prodn	1	1
UTL11	CAPACITY UTILIZATION - MANUFACTURING (SIC)	Capacity Util	1	1
CES277R	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - CONSTRUCTION (CES277/PI071)	Real AHE: const	5	400
CES278 R	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - MFG (CES278/PI071)	Real AHE: mfg	5	400
CES006	EMPLOYEES, NONFARM - MINING	Emp: mining	5	400
CES011	EMPLOYEES, NONFARM - CONSTRUCTION	Emp: const	5	400
CES017	EMPLOYEES, NONFARM - DURABLE GOODS	Emp: dble gds	5	400
CES033	EMPLOYEES, NONFARM - NONDURABLE GOODS	Emp: nondbles	5	400
CES046	EMPLOYEES, NONFARM - SERVICE-PROVIDING	Emp: services	5	400
CES048	EMPLOYEES, NONFARM - TRADE, TRANSPORT, UTILITIES	Emp: TTU	5	400
CES049	EMPLOYEES, NONFARM - WHOLESALE TRADE	Emp: wholesale	5	400
CES053	EMPLOYEES, NONFARM - RETAIL TRADE	Emp: retail	5	400
CES088	EMPLOYEES, NONFARM - FINANCIAL ACTIVITIES	Emp: FIRE	5	400
CES140	EMPLOYEES, NONFARM - GOVERNMENT	Emp: Govt	5	400
LHEL	INDEX OF HELP-WANTED ADVERTISING IN NEWSPAPERS (1967=100;SA)	Help wanted indx	2	1
LHELX	EMPLOYMENT: RATIO; HELP-WANTED ADS:NO. UNEMPLOYED CLF	Help wanted/emp	2	1
LHNAG	CIVILIAN LABOR FORCE: EMPLOYED, NONAGRIC.INDUSTRIES (THOUS.,SA)	Emp CPS nonag	5	400
LHUR	UNEMPLOYMENT RATE: ALL WORKERS, 16 YEARS & OVER (%,SA)	U: all	2	1
LHU680	UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS (SA)	U: mean duration	2	1
LHU5	UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5 WKS (THOUS.,SA)	U ¡ 5 wks	5	400
LHU14	UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS (THOUS.,SA)	U 5-14 wks	5	400
LHU15	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS + (THOUS.,SA)	U 15+ wks	5	400
LHU26	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS (THOUS.,SA)	U 15-26 wks	5	400
LHU27	UNEMPLOY.BY DURATION: PERSONS UNEMPL.27 WKS + (THOUS,SA)	U 27+ wks	5	400
CES151	AVG WKLY HOURS, PROD WRKRS, NONFARM - GOODS-PRODUCING	Avg hrs	1	1
CES155	AVG WKLY OVERTIME HOURS, PROD WRKRS, NONFARM - MFG	Overtime: mfg	2	1

Table A2 continued

Code	Long Description	Short Desc	TCode	Scale
HSNE	HOUSING STARTS:NORTHEAST (THOUS.U.)S.A.	HStarts: NE	4	1
HSMW	HOUSING STARTS:MIDWEST(THOUS.U.)S.A.	HStarts: MW	4	1
HSSOU	HOUSING STARTS:SOUTH (THOUS.U.)S.A.	HStarts: South	4	1
HSWST	HOUSING STARTS:WEST (THOUS.U.)S.A.	HStarts: West	4	1
FM1	MONEY STOCK: M1(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL$,SA)	M1	6	400
MZMSL	MZM (SA) FRB St. Louis	MZM	6	400
FM2	MONEY STOCK:M2(M1+O'NITE RPS,EURO$,G/P&B/D MMMFS&SAV&SM TIME DEP(BIL$,	M2	6	400
FMFBA	MONETARY BASE, ADJ FOR RESERVE REQUIREMENT CHANGES(MIL$,SA)	MB	6	400
FMRRA	DEPOSITORY INST RESERVES:TOTAL,ADJ FOR RESERVE REQ CHGS(MIL$,SA)	Reserves tot	6	400
FMRNBA	DEPOSITORY INST RESERVES:NONBORROWED,ADJ RES REQ CHGS(MIL$,SA)	Reserves nonbor	6	400
BUSLOANS	Commercial and Industrial Loans at All Commercial Banks (FRED) Billions $ (SA)	BUSLOANS	6	400
CCINRV	CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19)	Cons credit	6	400
FSDXP	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)	S&P div yield	2	1
FSPXE	S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%,NSA)	S&P PE ratio	2	1
HHSNTN	U. OF MICH. INDEX OF CONSUMER EXPECTATIONS(BCD-83)	Consumer expect	2	1
PMI	PURCHASING MANAGERS' INDEX (SA)	PMI	1	1
PMNO	NAPM NEW ORDERS INDEX (PERCENT)	NAPM new ordrs	1	1
PMDEL	NAPM VENDOR DELIVERIES INDEX (PERCENT)	NAPM vendor del	1	1
PMNV	NAPM INVENTORIES INDEX (PERCENT)	NAPM Invent	1	1
MOCMQ	NEW ORDERS (NET) - CONSUMER GOODS & MATERIALS, 1996 DOLLARS (BCI)	Orders (ConsGoods)	5	400
MSONDQ	NEW ORDERS, NONDEFENSE CAPITAL GOODS, IN 1996 DOLLARS (BCI)	Orders (NDCapGoods)	5	400

Table A3: Summary of Models

Name	Eq. #	Equation
		Benchmark Models for Inflation
AO		$\pi^Q_{t+4} = \pi^Q_t + u_{t+4}$
$UCSV$		$\pi^Q_t = \tau_t + u_t$, where $\tau_t = \tau_{t-1} + e_t$, $u_t = \sigma_{u,t}\eta_{u,t}$ and $e_t = \sigma_{e,t}\eta_{e,t}$ $\ln\sigma^2_{u,t} = \ln\sigma^2_{u,t-1} + v_{u,t}$, and $\ln\sigma^2_{e,t} = \ln\sigma^2_{e,t-1} + v_{e,t}$, $\eta_t = (\eta_{u,t}, \eta_{e,t})$ is $i.i.d.N(0, I_2)$ and $v_t = (v_{u,t}, v_{e,t})$ is $i.i.d.N(0, \gamma I_2)$, and η_t and v_t are independent with γ being a scalar parameter.
		Benchmark Model for IP and GDP growth
RW		$Y^Q_{t+1} = \mu + Y^Q_t + u_{t+1}$
		Autoregressive and Factor Autoregressive Models
$AR(p^Q_Y)$		$Y^Q_{t+1} = \mu + \sum_{k=0}^{p^Q_Y-1} \alpha_k Y^Q_{t-k} + u_{t+1}$
$FAR(p^Q_Y, p^Q_X)$	2.16	$Y^Q_{t+1} = \mu + \sum_{k=0}^{p^Q_Y-1} \alpha_k Y^Q_{t-k} + \sum_{k=0}^{p^Q_F-1} \beta_k F^Q_{t-k} + u_{t+1}$
		Restricted Autoregressive and Factor Autoregressive Models
$AR(p^Q_Y[r])$		$Y^Q_{t+1} = \mu + \alpha \sum_{k=0}^{p^Q_Y-1} w_k(\theta^Q_Y) Y^Q_{t-k} + u_{t+1}$
$FAR(p^Q_Y, p^Q_X)$	2.16	$Y^Q_{t+1} = \mu + \alpha \sum_{k=0}^{p^Q_Y-1} w_k(\theta^Q_Y) Y^Q_{t-k} + \beta \sum_{k=0}^{p^Q_F-1} w_k(\theta^Q_Y) F^Q_{t-k} + u_{t+1}$

Table continued on next page ...

Table A3 continued

Name	Eq. #	Equation
		ADL and Factor ADL Models
$ADL(p_Y^Q, p_X^Q)$	2.1	$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_X^Q-1} \beta_k X_{t-k}^Q + u_{t+1}$
$FADL(p_Y^Q, p_F^Q, p_X^Q)$	2.15	$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_F^Q-1} \beta_k F_{t-k}^Q + \sum_{k=0}^{p_X^Q-1} \gamma_k X_{t-k}^Q + u_{t+1}$
		ADL-MIDAS and Factor ADL-MIDAS models
$ADL-MIDAS(p_Y^Q, p_X^D)$	2.3	$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \beta \sum_{j=0}^{p_X^D-1} \sum_{i=1}^{N_D} w_{i+j*N^D}(\theta_X^D) X_{i,t-j}^D + u_{t+1}$
$ADL-MIDAS-M(p_Y^Q, p_X^Q)$	2.10	$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_X^Q-1} \beta_k X_{t-k}^Q(\theta_X^D) + u_{t+1}$
$FADL-MIDAS(p_Y^Q, p_F^Q, p_X^D)$	2.15	$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_F^Q-1} \beta_k F_{t-k}^Q + \gamma \sum_{j=0}^{p_X^D-1} \sum_{i=1}^{N_D} w_{i+j*N^D}(\theta_X^D) X_{i,t-j}^D + u_{t+1}$
$FADL-MIDAS-M(p_Y^Q, p_F^Q, p_X^Q)$		$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_F^Q-1} \beta_k F_{t-k}^Q + \sum_{k=0}^{p_X^Q-1} \gamma_k X_{t-k}^Q(\theta_X^D) + u_{t+1}$

Table A3 continued

Name	Eq. #	Equation
		Restricted ADL-MIDAS and Factor ADL-MIDAS models
$ADL(p_Y^Q[r], p_X^Q[r])$		$Y_{t+1}^Q = \mu + \alpha \sum_{k=0}^{p_Y^Q-1} w_k(\theta_Y^Q) Y_{t-k}^Q + \beta \sum_{k=0}^{p_X^Q-1} w_k(\theta_X^Q) X_{t-k}^Q + u_{t+1}$
$FADL(p_Y^Q[r], p_F^Q[r], p_X^Q[r])$		$Y_{t+1}^Q = \mu + \alpha \sum_{k=0}^{p_Y^Q-1} w_k(\theta_Y^Q) Y_{t-k}^Q + \beta \sum_{k=0}^{p_F^Q-1} w_k(\theta_F^Q) F_{t-k}^Q + \gamma \sum_{k=0}^{p_X^Q-1} w_k(\theta_X^Q) X_{t-k}^Q + u_{t+1}$
		Restricted ADL-MIDAS and Factor ADL-MIDAS models
$ADL-MIDAS(p_Y^Q[r], p_X^D)$		$Y_{t+1}^Q = \mu + \alpha \sum_{k=0}^{p_Y^Q-1} w_k(\theta_Y^Q) Y_{t-k}^Q + \beta \sum_{j=0}^{p_X^D-1} \sum_{i=1}^{N_D} w_{i+j*N^D}(\theta_X^D) X_{i,t-j}^D + u_{t+1}$
$ADL-MIDAS-M(p_Y^Q[r], p_X^Q[r])$	2.11	$Y_{t+1}^Q = \mu + \alpha \sum_{k=0}^{p_Y^Q-1} w_k(\theta_Y^Q) Y_{t-k}^Q + \beta \sum_{k=0}^{p_X^Q-1} w_k(\theta_X^Q) X_{t-k}^Q(\theta_X^D) + u_{t+1}$
$FADL-MIDAS(p_Y^Q[r], p_F^Q[r], p_X^D)$		$Y_{t+1}^Q = \mu + \alpha \sum_{k=0}^{p_Y^Q-1} w_k(\theta_Y^Q) Y_{t-k}^Q + \beta \sum_{k=0}^{p_F^Q-1} w_k(\theta_F^Q) F_{t-k}^Q + \gamma \sum_{j=0}^{p_X^D-1} \sum_{i=1}^{N_D} w_{i+j*N^D}(\theta_X^D) X_{i,t-j}^D + u_{t+1}$
$FADL-MIDAS-M(p_Y^Q[r], p_F^Q[r], p_X^Q[r])$		$Y_{t+1}^Q = \mu + \alpha \sum_{k=0}^{p_Y^Q-1} w_k(\theta_Y^Q) Y_{t-k}^Q + \beta \sum_{k=0}^{p_F^Q-1} w_k(\theta_F^Q) F_{t-k}^Q + \gamma \sum_{k=0}^{p_X^Q-1} w_k(\theta_X^Q) X_{t-k}^Q(\theta_X^D) + u_{t+1}$
		Factor ADL-MIDAS with Lead J
$FADL-MIDAS(p_Y^Q, p_F^Q, p_X^D, J_X^D)$	2.18	$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_F^Q-1} \beta_k F_{t-k}^Q$ $+\gamma[\sum_{i=0}^{J_X^D-1} w_i(\theta_X^D) X_{J_X^D-i,t+1}^D + \sum_{j=0}^{p_X^D-1} \sum_{i=0}^{N_D-1} w_{i+j*N^D}(\theta_X^D) X_{N_D-i,t-j}^D] + u_{t+1},$