Should macroeconomic forecasters use daily financial data and how?*

Elena Andreou[†] **Eric Ghysels**[‡] **Andros Kourtellos**[§]

First Draft: May 2009
This Draft: November 2, 2010

Abstract

We introduce easy to implement regression-based methods for predicting quarterly real economic activity that use daily financial data and rely on forecast combinations of MIDAS regressions. Our analysis is designed to elucidate the value of daily information in terms of improving traditional forecasts based on aggregated data and provide real-time forecast updates of the current (nowcasting) and future quarters. Our empirical study covers both a long historical period as well as the recent financial crisis. While on average the predictive ability of all models worsens substantially following the financial crisis, the models we propose do not suffer as much losses as the traditional ones.

*The first author acknowledges support of the European Community FP7/2008-2012 ERC grant 209116. 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, Jonathan H. Wright, and Michael McCracken 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, the CIRANO/CIREQ Financial Econometrics Conference, the MEG Conference, the ESEM Meeting, the EC^2 Conference - Aarhus, the NBER Summer Institute, the NBER/NSF Time Series Conference at Duke University, the RES conference, and the 6th ECB Workshop on Forecasting Techniques for comments at various versions of this paper. We also thank Constantinos Kourouyiannis, Michael Sockin, Athanasia Petsa, and Elena Pilavaki for providing excellent research assistance on various parts of the paper.

[†]Department of Economics, University of Cyprus, P.O. Box 537, CY 1678 Nicosia, Cyprus, e-mail: `elena.andreou@ucy.ac.cy`.

[‡]Department of Economics, University of North Carolina, Gardner Hall CB 3305, Chapel Hill, NC 27599-3305, USA, and Department of Finance, Kenan-Flagler Business School, e-mail: `eghysels@unc.edu`.

[§]Department of Economics, University of Cyprus, P.O. Box 537, CY 1678 Nicosia, Cyprus, e-mail: `andros@ucy.ac.cy`

1 Introduction

Theory suggests that the forward looking nature of financial asset prices should contain information about the future state of the economy and therefore should be considered as extremely relevant for macroeconomic forecasting. There is 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, ignoring the high frequency of financial series. 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 environment one faces essentially two key challenges: (1) how to handle the mixture of sampling frequencies i.e. matching daily (or an arbitrary higher frequency such as potentially intra-daily) financial data with quarterly (or monthly) macroeconomic series when one wants to predict short as well as relatively long horizons, like one year ahead, and (2) how to summarize the information or extract the common components from the vast cross-section of daily financial series that span the five major classes of assets - commodities, corporate risk, equities, fixed income and foreign exchange. In this paper we address both challenges.

Not using the readily available high frequency data such as daily financial predictors to perform quarterly forecasts has two important implications: (1) one foregoes the possibility of using real time daily, weekly or monthly updates of quarterly macro forecasts and (2) one looses information through temporal aggregation. 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] Therefore, state space models are far more complex in terms of specification, estimation and computation

[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.

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 specifying the dynamics of all the series involved. This approach is often feasible when dealing with a small system (such as, for instance, Aruoba, Diebold, and Scotti (2009) which involves only 6 series). Instead, our analysis deals with a larger number of daily variables (ranging from 65 to 966) and therefore the approach we propose is regression-based and reduced form - notably not requiring to model the dynamics of each and every daily predictor series and estimate a large number of parameters. Consequently, our approach deals with a parsimonious predictive equation, which in most cases leads to improved forecasting ability. In order to deal with data sampled at different frequencies we use 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]

Using standard regression models where the regressors are aggregated to some low frequency, such as for instance with financial aggregates (that are available at higher frequencies), is also problematic in terms of estimation. Andreou, Ghysels, and Kourtellos (2010a) show that the estimated slope coefficient of a regression model that imposes a standard aggregation scheme (and ignore the fact that processes are generated from a mixed data environment) yield asymptotically inefficient (at best) and in many cases inconsistent estimates. Both inefficiencies and inconsistencies can have adverse effects on forecasting.

A number of recent papers have documented the advantages of using 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

[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 (2010a). The original work on MIDAS focused on volatility predictions, see also Alper, Fendoglu, and Saltoglu (2008), Chen and Ghysels (2010), 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 or a few daily financial series, see e.g. Ghysels and Wright (2009), Hamilton (2006), Monteforte and Moretti (2009) and Tay (2006).

in large cross-sections of high frequency financial data, nor the potential usefulness of such series for real-time forecast updating.

The gains of real-time forecast updating, sometimes called nowcasting when it applies to current quarter assessments, have also been documented in the literature and are of particular interest to policy makers.[6] These studies use 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 high frequency data feeds. More importantly, we show that MIDAS regressions can be extended beyond nowcasting the current quarter to produce direct forecasts multiple quarters ahead.

To deal with the potential large cross-section of daily series we propose two approaches: (1) We extract a small set of daily financial factors from a large cross-section of around one thousand financial time series, which cover the five aforementioned main classes of assets - Commodities, Corporate Risk, Equities, Foreign Exchange, and Government Securities (fixed income). (2) We apply forecast combination methods for these daily financial factors as well as a relatively smaller cross-section of individual daily financial predictors proposed in the literature. Forecast combinations provide robust forecasts for a large number of predictors as well as models.

In Figure 1 we provide a succinct preview of the forecasting gains due to the use of daily financial data to predict quarterly US real Gross Domestic Product (GDP) growth one quarter ahead. The three boxplots display the forecasting performance measured in terms of Mean Square Forecast Errors (MSFE), using a cross-section of financial series, based on three methods: (1) traditional models using quarterly/aggregated financial series, (2) MIDAS models using daily financial data and (3) MIDAS models with using daily leads corresponding to nowcasting.[7] Our results pertain to forecasting real GDP growth during the turbulent times of the financial crisis, namely forecasting US economic activity for the

[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.

[7]A boxplot displays graphically numerical data using some key statistics such as quartiles, medians etc. The particular representation we have chosen has the bottom and top of the box as the lower and upper quartiles, and the band near the middle of the box is the median. The ends of the whiskers represent the lowest datum still within 1.5 times the interquartile range (IQR) of the lower quartile, and the highest datum still within 1.5 IQR of the upper quartile. The plus signs could be viewed as outliers if the RMSFE in population were normally distributed. In our application the plus signs at the right of the box are very good forecasts, those at the left are very poor ones.

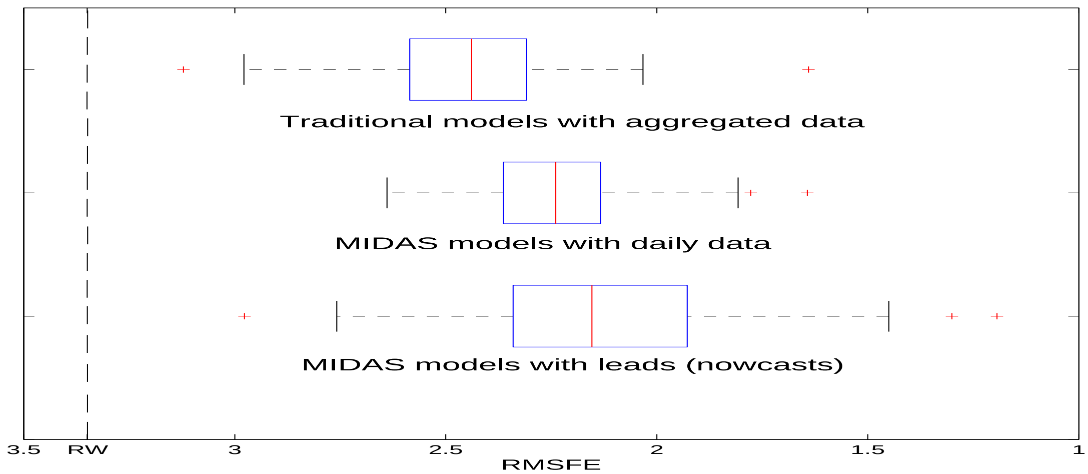


Figure 1: Forecasting Performance One Quarter Ahead US Real GDP Growth

period 2006-2008. Each point in the cross-section pertains to the forecast of a single financial series.

Deferring the details to later - the first boxplot involves a cross-section of 93 financial series, aggregated at the quarterly frequency. The 93 series are the typical Commodities, Corporate Risk, Equities, Foreign Exchange, and Government Securities (fixed income) series most of which are proposed as the most important predictors in the literature. Hence, the first boxplot relates to the standard practice of using aggregated data and thereby foregoing the information of financial series at daily frequency. The second boxplot replaces the cross-section of 93 quarterly financial series with their corresponding daily observations. Finally, the third boxplot contains a nowcast of real GDP growth two months into the quarter, so one has the equivalent of two months of real-time daily data to improve predictions. The plots pertain to the root mean squared forecast errors (RMSFE), which means that small values are the best forecast performances. For that reason the scale is reversed, from large to small such that moving to the right corresponds to better outcomes. The vertical line RW is the random walk forecast benchmark. We observe a substantial shift of the cross-sectional MSFE distribution representing the forecast improvement as we move from the first to the second boxplot. This shift shows the forecast gains when we use MIDAS regression models and replace the quarterly aggregates of financial assets with their corresponding daily measures. The final boxplot shows even further improvements in MSFE when we use MIDAS regressions with leads that also exploit the flow of available daily financial information within the quarter. More precisely, we extend the forecaster's information set by using financial information at the end of the second month of a quarter to make a forecast. These boxplots are illustrative and provide a preview of our findings, showing not only the important gains in forecasting using daily financial data but also the additional flexibility of updating forecasts with the steady flow of daily data. The gains observed in the boxplots can be improved even further when we use forecast combination methods that attach higher (lower) weight to models with lower (higher) MSFE. It is the purpose of this paper to explain how these gains are achieved.

The paper is organized as follows. In section 2 we describe the MIDAS regression models. Section 3 discusses the quarterly and daily data. In section 4 we present the factor analysis and forecast combination methods. In section 5 we present the empirical results, which includes comparisons of MIDAS models with traditional models using aggregated data as well as with various benchmark models including survey data. Section 6 concludes.

2 MIDAS regression models

Suppose we wish to forecast a variable observed at some low frequency, say quarterly, denoted by Y^Q_{t+1}, such as for instance, real GDP growth and we have at our disposal financial series that are considered as useful predictors. At the outset we should note that our methods are of general interest beyond the application of the current paper that focuses on quarterly economic activity forecasts. Namely, very often we face the problem of forecasting a low frequency variable using predictors observed at relatively higher frequencies.

Denote by X^Q_t a quarterly aggregate of a financial predictor series (the aggregation scheme being used is, say, averaging of the data available daily). One conventional approach, in its simplest form, is to use a so called Augmented Distributed Lag, $ADL(p^Q_Y, q^Q_X)$, regression model:

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

which involves p^Q_Y lags of Y^Q_t and q^Q_X lags of X^Q_t. This regression is fairly parsimonious as it only requires $p^Q_Y + q^Q_X + 1$ regression parameters to be estimated. Assume now that we would like to use instead the daily observations of the financial predictor series X_t. Denote $X^D_{N_D-j,t}$, the j^{th} day counting backwards in quarter t. Hence, the last day of quarter t corresponds with $j = 0$ and is therefore $X^D_{N_D,t}$. A naive approach would be to estimate - in the case of $p^Q_Y = q^Q_X = 1$ the regression model:

$$Y^Q_{t+1} = \mu + \alpha_1 Y^Q_t + \sum_{j=0}^{N_D-1} \beta_{1,j} X^D_{N_D-j,t} + u_{t+1} \tag{2.2}$$

where N_D denotes the daily lags or the number of trading days per quarter. This is an unappealing approach because of parameter proliferation: when $N_D = 66$, we have to estimate 68 coefficients. A MIDAS regression model solves this problem by hyper-parameterizing the polynomial lag structure in the above equation, yielding what we will call a $ADL - MIDAS(p^Q_Y, q^D_X)$ regression:

$$Y^Q_{t+1} = \mu + \sum_{j=0}^{p^Q_Y-1} \alpha_{j+1} Y^Q_{t-j} + \beta \sum_{j=0}^{q^D_X-1} \sum_{i=0}^{N_D-1} w_{i+j*N_D}(\theta^D) X^D_{N_D-i,t-j} + u_{t+1}, \tag{2.3}$$

where the weighting scheme, $w(\theta^D)$, involves a low dimensional vector of unknown parameters. Note that in this model to simplify notation, we take quarterly blocks of daily data as lags.

Following Ghysels, Santa-Clara, and Valkanov (2006) and Ghysels, Sinko, and Valkanov (2006), we use a two parameter exponential Almon lag polynomial

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

with $\theta^D = (\theta_1, \theta_2)$. This approach allows us to obtain a linear projection of high frequency data X^D_t onto Y^Q_t with a small set of parameters namely p^Q_Y+q^Q_X+3. Note that the exponential Almon polynomial yields a general and flexible parametric function of data-driven weights. It worth noting that for different values of θ_1 and θ_2 we obtain different shapes of the weighting scheme and for $(\theta_1 = \theta_2) = 0$ in (2.4) we obtain the flat weights namely $w_j(\theta^D)$=$1/N_D$.[8]

[8]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).

2.1 Temporal aggregation issues

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 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 traditional temporal aggregation, it may not be optimal for time series data which most often exhibit a downward sloping memory decay structure, 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 the shape of the weights.

We can relate MIDAS models to the temporal aggregation literature and traditional models by considering two additional specifications for the quarterly lags. First, define the following filtered parameter-driven *quarterly* variable

$$X_t^Q(\theta_X^D) \equiv \sum_{i=0}^{N^D-1} w_i(\theta_X^D) X_{N_D-i,t}^D, \tag{2.5}$$

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:

$$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_X^Q-1} \beta_k X_{t-k}^Q(\theta_X^D) + u_{t+1} \tag{2.6}$$

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

$$Y_{t+1}^Q = \mu + \alpha \sum_{k=0}^{p_Y^Q-1} w_k(\theta_Y^Q) Y_{t-k}^Q + \beta \sum_{k=0}^{p_X^Q-1} w_k(\theta_X^Q) X_{t-k}^Q(\theta_X^D) + u_{t+1}. \tag{2.7}$$

Both equations (2.6) and (2.7) 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 (2.6) does not restrict the coefficients of the quarterly lags, equation (2.7) 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]

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 how the regression in (2.3) relates to the more traditional approach involving the Kalman filter. 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 in general a MIDAS regression model 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. As discussed in Bai, Ghysels, and Wright (2009), the aggregation weights have a structure very similar to the ones appearing in the MIDAS regression (2.7). 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.[10]

Second, the Kalman filter, while clearly optimal as far as linear projections in a Gaussian setting go, has two main disadvantages (1) it is more prone to specification errors as a full system of equations 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 misspecification. 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, which is not so appealing when dealing with hundreds of daily financial time series - as we do below.

[9]The multiplicative MIDAS scheme was originally suggested for purpose of dealing with intra-daily seasonality in high frequency data, see Chen and Ghysels (2010).

[10]Bai, Ghysels, and Wright (2009) discusses both the cases where the mapping is exact and the approximation errors in cases where the MIDAS does not coincide with the Kalman filter.

2.2 Nowcasting and leads

Giannone, Reichlin, and Small (2008), among others, have formalized the process of updating forecasts as new releases of data become available, using the terminology of nowcasting for such updating. In particular, using a dynamic factor state-space model and the Kalman filter, they model the joint dynamics of real GDP and the monthly data releases and propose solutions for estimation when data have missing observations at the end of the sample due to non-synchronized publication lags (the so called jagged/ragged edge problem).

In this paper we propose an alternative reduced form strategy based on MIDAS regression with *leads* by incorporating real-time information using daily financial variables. There are two important differences between nowcasting (using the Kalman filter) and MIDAS with leads. Before we elaborate on these two differences we explain first what is meant by MIDAS with leads.

Suppose we are two months into quarter $t+1$, hence the end of February, May, August or November, and our objective is to forecast quarterly economic activity. In practice we often have a monthly release of macroeconomic data within the quarter and the equivalent of at least 44 trading days (i.e. two months) of daily financial data. This means that if we stand on the last day of the second month of the quarter and wish to make a forecast for the current quarter we could use 44 'leads' (with respect to quarter t data/lags) of daily data.

Traditional forecasting considers data available at the end of quarter t. The notion of leads pertains to the fact that we use information between t and $t+1$. Consider the ADL-MIDAS regression in equation (2.3), which allows for J_X^D daily leads for the daily predictor, expressed in multiples of months, $J_X^D = 1$ and 2. Then we can specify the $ADL - MIDAS(p_Y^Q, p_X^D, J_X^D)$ model:

$$\begin{aligned} Y_{t+1}^Q &= \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \gamma[\sum_{i=0}^{J_X^D-1} \tilde{w}_i(\theta_X^D) X_{J_X^D-i,t+1}^D \\ &\quad + \sum_{j=0}^{p_X^D-1} \sum_{i=0}^{N_D-1} w_{i+j*N^D}(\theta_X^D) X_{N_D-i,t-j}^D] + u_{t+1}, \end{aligned} \tag{2.8}$$

There are various ways to hyper-parameterize the lead and lag MIDAS polynomials. Along with a complete list of MIDAS regression models this is discussed in the Appendix B3 companion document Technical Appendix (see Andreou, Ghysels, and Kourtellos (2010b)) -

henceforth we will refer to this as the online Appendix.

The approach we propose mimics the process of nowcasting and generalizes it, while also avoiding the aforementioned disadvantages of the state space and the Kalman filter - that is the proliferation of parameters, the proneness to model specification errors and the numerical challenges. The first difference between nowcasting and MIDAS with leads can be explained as follows. Nowcasting refers to within-period updates of forecasts. An example would be the frequent updates of *current* quarter real GDP forecasts. MIDAS with leads can be viewed as updates - timed as frequently - of not only current quarter real GDP forecasts, but any future horizon real GDP forecast (i.e. over several future quarters). Of course, when MIDAS with leads applies to updates of current quarter forecasts - it coincides with the exercise of nowcasting.

The second difference between typical applications of nowcasting and MIDAS with leads pertains to the jagged/ragged edge nature of macroeconomic data. Nowcasting addresses the real-time nature of macroeconomic releases directly - the nature being jagged/ragged edged as it is referred to due to the unevenly timed releases. Hence, the release calendar of macroeconomic news plays an explicit role in the specification of the state space measurement equations. In MIDAS regressions with leads we do not constantly update the low frequency series - that is the macroeconomic data. Our approach puts the trust into the financial data in absorbing and impounding the latest news into asset prices. There is obviously a large literature in finance on how announcements affect financial series (early examples include Urich and Wachel (1984), Summers (1986), Wasserfallen (1989), among others). The daily flow of information is absorbed by the financial data being used in MIDAS regressions with leads - which greatly simplifies the analysis. The Kalman filter in the context of nowcasting has the advantage that one can look at how announcement 'shocks' affect forecasts. While it may not be directly apparent - MIDAS regressions with leads can provide similar tools. It suffices to run a MIDAS regressions with leads using prior and post-announcement financial data and analyze the changes in the resulting forecasts (see for example Ghysels and Wright (2009) for further discussion).

It should also be noted that traditional nowcasting now only deals with the very detailed calendar of macroeconomic releases, it also in principle keeps track of data revisions. The MIDAS with leads approach we implement has the advantage of using financial data that are observed without measurement error and are not subject to revisions as opposed to most macroeconomic indicators.

To conclude, we should also note that MIDAS with leads differs from the MIDAS regressions involving “leading indicator” series, as in Clements and Galvão (2009) in that the latter employs a (monthly) leading indicator series *aligned* with quarterly real GDP growth data. In contrast our model in (2.8) is based on daily financial indicators, which observed without any measurement errors.

3 Data

We focus on forecasting the US quarterly real GDP growth rate. We are interested in quarterly forecasts of real GDP growth as it is one of the key macroeconomic measures in the literature. Moreover, policy makers report quarterly real GDP forecasts, see for instance the Fed’s Greenbook forecasts. Similarly, it is one of the variables covered in most surveys of macroeconomic forecasts such as, for instance, the Survey of Professional Forecasters, among others.

We study two sample periods of US real GDP. A longer sample period from 1/1/1986-31/12/2008 (of 92 quarters) and a shorter subperiod from 1/1/1999-31/12/2008 (of 40 quarters). There are at least three reasons we choose to emphasize the shorter sample of 1999. First, this period provides a set of daily financial predictors that is new 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 spreads), term structure variables (e.g. inflation compensation series or breakeven inflation rates), equity measures (such as the implied volatility of S&P500 index option (VIX), the Nasdaq 100 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 (see, for instance, the comprehensive review in Stock and Watson (2003)) but have also been recently informally monitored by policy makers and practitioners even on a daily basis to forecast inflation and economic activity. Examples include the breakeven inflation rates discussed during the Federal Open Market Committee (FOMC) meetings and the VIX often coined as the stock market fear-index.

Second, the data-rich environment of the 1999 sample allows us to study the role of a large cross-section of financial predictors available at the daily frequency in improving traditional forecasts of economic activity. Typically, these forecasts are based on methods that rely primarily on macroeconomic variables, with their availability limited to monthly or quarterly frequency. In contrast, we work at the daily frequency and summarize the large cross-sectional information into a few daily financial factors. In fact, one of the popular approaches in forecasting real GDP growth is based on quarterly macroeconomic factor models (e.g. Forni, Hallin, Lippi, and Reichlin (2005), Stock and Watson (2007), and Stock and Watson (2008a)). Building on this line of research and as we discuss in detail in Section 4.1 we extend the toolbox of forecasters by constructing a set of financial factors at the daily frequency and evaluate their predictive ability.

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. Therefore, we take the challenge of predicting economic growth in a period that many models and methods did not provide substantial forecasting gains over simple models.

We use three databases observed at two different sampling frequencies: one quarterly database of macroeconomic indicators and two daily databases of financial indicators. We refer to the indicators based on the daily databases as daily financial assets. The data sources for the quarterly and daily series are Haver Analytics, a data warehouse that collects the data series from their original sources (such as the Federal Reserve Board (FRB), Chicago Board of Trade (CBOT) and others), the Global Financial Database (GFD) and FRB, unless otherwise stated. All the series were transformed in order to eliminate trends so as to ensure stationarity. Details of the transformations can be found in a the online Appendix, see Andreou, Ghysels, and Kourtellos (2010b).

The first dataset consists of 69 macroeconomic quarterly series of real output and income, capacity utilization, employment and hours, price indices, money, etc., described in detail in the Technical Appendix. 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.[11] We use this dataset to extract the quarterly factors,

[11]The excluded variables from the quarterly factor analysis are the foreign exchange rates of Swiss Franc,

which we will call macro or real factors.

The second database is a comprehensive daily dataset, which covers a large cross-section of 988 daily series from 1/1/1999-31/12/2008 (1777 trading days) for five classes of financial assets. We use this large dataset to extract a small set of daily financial factors. The five classes of daily financial assets are: (i) the Commodities class which includes 241 variables such as US individual commodity prices, commodity indices and futures; (ii) the Corporate Risk category includes 210 variables such as yields for corporate bonds of 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 such as major international currency rates 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 Table B1 of the online Appendix, which also includes information about transformations and data source.

We also create a third smaller daily database, described in Table A1 appearing at the end of the paper, which is a subset of the aforementioned large cross-section. It includes 93 daily predictors for the sample of 1999 (2251 trading days) and 65 daily predictors for the sample of 1986 due to data availability (4584 trading days) from the above five categories of financial assets.[12] These daily predictors are proposed in the literature as good predictors of economic growth. Describing briefly these daily predictors we categorize them into five classes: (1) Forty commodity variables which include commodity indices, prices and futures (suggested, for instance, in Edelstein (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&P 500 Implied

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.

[12] Note that the difference in the total number of trading days between the smaller sample of 93 variables and the larger one of 988 series is due to fact that the former involves less missing observations when balancing the short cross-section.

Volatility (VIX for the 1999 sample and VXO for the 1986 sample) - 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 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) and (1989), Harvey (1988) and (1989b), 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, described in Aruoba, Diebold, and Scotti (2009), which can also be considered as a daily factor based on 6 US macroeconomic variables of mixed frequency. The ADS index, which includes series other than financial, complements our daily factors extracted from our large cross-section of exclusively financial variables.

4 Implementation issues

In this section we develop two strategies to address the use of a large cross-section of high frequency financial data for forecasting key macroeconomic variables.

The first strategy involves extracting factors from two large cross-sections observed at different frequencies described in section 3. Namely, we extract (i) quarterly (real) macroeconomic factors from the quarterly database and (ii) daily financial factors from our large daily database of 988 assets. Both the daily financial factors and quarterly macroeconomic factors, along with lagged real GDP growth, are used in MIDAS regressions as predictors of real GDP growth.[13]

The second approach involves forecast combinations of MIDAS regressions with a single financial asset based on the smaller daily database of 93 assets (sample of 1999) or 65 assets

[13] A more ambitious approach would be to extract factors from a large mixed frequency data set. However, this would require several technical innovations, which are beyond the scope of this paper and therefore leave this for future research.

(sample of 1986). We use the two approaches as complementary in the sense that we employ forecast combinations of both daily financial assets and daily financial factors. Forecast combinations deal explicitly with the problem of model uncertainty by obtaining evidentiary support across all forecasting models rather than focusing on a single model.

4.1 Daily and quarterly factors

There is a large recent literature on dynamic factor model techniques that are tailored to exploit a large cross-sectional dimension; see for instance, Bai and Ng (2002) and (2003), Forni, Hallin, Lippi, and Reichlin (2000) and (2005), Stock and Watson (1989) and (2003), among many others. The idea is that a handful of unobserved common factors are typically sufficient to capture the covariation among economic time series. Typically, the literature estimates these factors at quarterly frequency using a large cross-section of time-series. Then these estimated factors augment the standard AR and ADL models to obtain the Factor AR (FAR) and Factor ADL (FADL) models, respectively. Stock and Watson (2002b) and (2006) find that such models based on the estimated factors extracted from large datasets can improve forecasts of real economic activity and other key macroeconomic indicators based on low-dimensional forecasting regressions.

Following this literature we do two things. First, we construct quarterly factors from our dataset of 69 quarterly mainly (real) macroeconomic series to augment the MIDAS regression models with quarterly factors. Second we construct *daily* financial factors extracted from all 988 daily financial series as well as more homogeneous *daily* factors extracted separately from each of the 5 classes of financial assets described in the previous section. Subsequently, we investigate their predictive ability by using these daily factors as daily predictors in all the MIDAS regression models. Due to the small time series sample we do not consider more than one daily factor in a forecasting equation, but use again forecast combinations of MIDAS regressions based on the various daily financial factors.[14]

In particular, using the quarterly common factors we extend the MIDAS regression models.

[14]In large time series settings one could potentially run all the daily and quarterly factors in one single MIDAS regression.

For instance, equation (2.3) generalizes to the $FADL-MIDAS(p_Y^Q, p_F^Q, q_X^D)$ model

$$\begin{aligned} Y_{t+1}^Q &= \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_F^Q-1} \beta_k F_{t-k}^Q \\ &+ \gamma \sum_{j=0}^{q_X^D-1} \sum_{i=0}^{N_D-1} w_{i+j*N^D}(\theta_X^D) X_{N_D-i,t-j}^D + u_{t+1} \end{aligned} \tag{4.1}$$

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 (2.6). Note also that the above equation simplifies to the traditional FADL 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.

It is important to note that MIDAS regressions with leads, discussed in section 2.2, can also have factors as regressors. In such cases, daily leads of financial factors are used, while the past quarterly factors remain the same. As noted earlier, this approach is different from the so called jagged/ragged edge problem, where the calendar of macroeconomic releases drives the updating scheme of a Kalman filtering algorithm. Our approach assumes that financial markets react relatively more quickly to economic and other conditions than other markets and therefore the latest news is incorporated into asset prices while the macroeconomic factors and lagged real GDP growth remain unrevised. A good example of this is the financial crisis that started with the subprime mortgage defaults in the US. Most macroeconomic real activity indicators remained stable even months after the Lehman failure, while in particular the credit markets collapse predicted major economic hardship ahead.

The next issue is how we construct the factors. We estimate both the quarterly macroeconomic factors and the daily financial factors using a Dynamic Factor Model (DFM) with time-varying factor loadings, which is given by the following static representation:

$$\begin{aligned} X_t &= \Lambda_t F_t + e_t \\ F_t &= \Phi_t F_{t-1} + \eta_t \\ e_{it} &= a_{it}(L) e_{it-1} + \varepsilon_{it}, \quad i = 1, 2, ..., N, \end{aligned} \tag{4.2}$$

where $X_t = (X_{1t}, ..., X_{Nt})'$, F_t is the r-vector of static factors, Λ_t is a $N \times r$ matrix of factor loadings, $e_t = (e_{1t}, ..., e_{Nt})'$ is an N-vector of idiosyncratic disturbances, which can be serially correlated and (weakly) cross-sectionally correlated.[15]

We choose this particular factor model for two main reasons. First, it allows for the possibility that the factor loadings change over time (compared to the standard DFMs), which may address potential instabilities during our sample period (see Theorem 3, p. 1170, in Stock and Watson (2002a)). Hence, the extracted common factors can be robust to instabilities in individual time series, if such instability is small and sufficiently dissimilar among individual variables, so that it averages out in the estimation of common factors. Second, the errors, ε_{it} are allowed to be conditionally heteroskedastic and serially and cross-correlated (see Stock and Watson (2002a) for the full set of assumptions). These assumptions are useful given that most daily financial time series exhibit GARCH type dynamics.

Under these assumptions we estimate the factors using a principal component method that involves cross-sectional averaging of the individual predictors. An advantage of this estimation approach is that it is nonparametric and therefore we do not need to specify any additional auxiliary assumptions required by state space representations especially in view of the dynamic structure of daily financial processes.[16] DFM using principal components yields consistent estimates of the common factors if $N \to \infty$ and $T \to \infty$. The condition $\sqrt{T}/N \to 0$ ensures that the estimated coefficients of the forecasting equations (e.g. FADL-MIDAS in equation 4.2) are consistent and asymptotically Normal with standard errors, which are not subject to the estimation error from the DFM model estimation in the first stage.[17]

There are alternative approaches to choosing the number of factors. One approach is to use the information criteria (ICP) proposed by Bai and Ng (2002). For the quarterly macroeconomic factors ICP criteria yield two factors for the period 1999:Q1-2008:Q8, denoted by F_1^Q and F_2^Q. These first two quarterly factors explain 36% and 12%, respectively, of the total variation of the panel of quarterly variables. The first quarterly factor correlates

[15]The static representation in equation (4.2) can be derived from the DFM assuming finite lag lengths and VAR factor dynamics in the DFM in which case F_t contains the lags (and possibly leads) of the dynamic factors. Although generally the number of factors from a DFM and those from a static one differ, we have that $r = d(s + 1)$ where r and d are the numbers of static and dynamic factors, respectively, and s is the order of the dynamic factor loadings. Moreover, empirically static and dynamic factors produce rather similar forecasts (see Bai and Ng (2008)).

[16]State space models and the associated Kalman filter are based on linear Gaussian models. Non-Gaussian state space models are numerically much more involved, see e.g. Smith and Miller (1986), Kitagawa (1987), and the large subsequent literature - see the recent survey of Johannes and Polson (2006). Needless to say that each and every (state and measurement) equation requires explicit volatility dynamics in such extensions. This greatly expands the parameter space - as discussed earlier.

[17]Although the parametric AR assumption for F_t and e_{it} is not needed to estimate the factors, such assumptions can be useful when discussing forecasts using factors.

highly with Industrial Production and Purchasing Manager's index whereas the second quarterly factor correlates highly with Employment and the 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 (2009) that use a different panel of US data. 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 20 aggregated financial series do not seem to play an important role for extracting the first two factors for the period 1999:Q1-2008:Q4.

For the daily financial factors we find that all three ICP criteria always suggest the maximum number of factors. Therefore to choose the number of daily factors we assess the marginal contribution of the k^{th} principal component in explaining the total variation. We opt to use 5 daily factors in all exercises since we have found that overall this number explains a sufficiently large percentage of the cross-sectional variation. Panel A of Table 1 shows the standardized eigenvalues for the whole sample period for 5 daily factors extracted using the cross-section of 988 predictors, F^D_{ALL}, as well as the factors extracted from the 5 categories of financial assets described above: $F^D_{CLASS} = (F^D_{COMM}, F^D_{CORP}, F^D_{EQUIT}, F^D_{FX}$, and $F^D_{GOV}))$. As we will explain in the following section we employ forecast combinations of these daily factors rather than forecasts based on a particular daily factor. By doing so we shift the focus of the analysis from unconditional statements about the number of factors to conditional statements about the predictive ability of daily factors.

Nevertheless one issue is the stability of eigenvalues. What if these eigenvalues are unstable over the evaluation period? Do these 5 daily financial factors capture sufficiently the covariation among economic time series at any point of time in the evaluation period? To assess the stability of eigenvalues we computed the recursive eigenvalues for the first five principal components during our evaluation period of 2006-2008 (they appear in Figure B2 of the companion document Andreou, Ghysels, and Kourtellos (2010b)). The eigenvalues appear stable with the exception of some mild instability towards the end of the sample, especially for the eigenvalues of F^D_{CORP}. The first principal component in the five classes appears to capture at least 39% in all F^D_{CLASS} cases and as much as 79%, in the case of F^D_{EQUIT}, of the total variation. We therefore conclude that the first 5 daily financial factors extracted from all assets as well as those extracted from the 5 homogeneous classes of assets are sufficient to explain most of the variation in the data at any point of time in our evaluation period.

Figure 2 and Figure 3 present the time series plots of the first five daily financial factors using all 988 predictors, F^D_{ALL}, and the first daily factor from each of the five classes of assets, F^D_{CLASS}, respectively. In general, most of the five daily factors are characterized by volatility clustering and with recent high volatility period. Notable exceptions are $F^D_{ALL,5}$ and $F^D_{CORP,1}$ that are dominated by a strong cyclical component and $F^D_{ALL,2}$, $F^D_{ALL,3}$ and $F^D_{ALL,4}$ that exhibit a recent period of clustered large negative returns.

Next, we label the five daily financial factors extracted from all assets, F^D_{ALL}, by identifying which of the five classes of assets determine a large portion of their variation. Panel B of Table 1 shows the composition of the sum of squared loadings for the five daily factors based on all assets. Figure 4 presents the corresponding recursive time-series plots of the sum of squared loadings for the evaluation period. While the composition of $F^D_{ALL,1}$ appears rather stable this is not true for the other four factors, especially for $F^D_{ALL,3}$ and $F^D_{ALL,4}$. $F^D_{ALL,1}$ appears to load heavily on Government Securities and to less extend to Corporate Risk. Figure 4(b) shows that $F^D_{ALL,2}$ loads heavily on Equity until about the Lehman Brothers' fallout, which is viewed as the heart of the financial crisis. Then we see that $F^D_{ALL,2}$ starts to load on other assets such as Commodities, Government, and Corporate Risk. Figures 4(c)-(d) show that the composition of $F^D_{ALL,3}$ and $F^D_{ALL,4}$ changes dramatically. $F^D_{ALL,5}$ appears to load primarily on Corporate Risk and Government Securities.

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 bond risk premia.

4.2 Forecast combinations

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 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, Hendry and Clements (2004) argue that under certain conditions forecast combinations provide robust forecasts against deterministic structural breaks when individual forecasting models are misspecified while 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, forecast combinations 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 of the individual forecasts.

In this paper we focus on the Squared Discounted MSFE forecast combinations method, which delivers the highest forecast gains relative to other methods in our samples; see also Stock and Watson (2004) and (2008b). This method accounts for the historical performance of each individual by computing the combination forecast weights that are inversely proportional to the square of the discounted MSFE (henceforth denoted 2DiscMSFE) with a high discount factor attaching greater weight to the recent forecast accuracy of the individual models. More generally, the weights are given as follows.

$$\widehat{\omega}_{i,t} = \frac{\left(\lambda_{i,t}^{-1}\right)^{\kappa}}{\sum_{j=1}^{n} (\lambda_{j,t}^{-1})^{\kappa}} \tag{4.3}$$

$$\lambda_{i,t} = \sum_{\tau=T_0}^{t-h} \delta^{t-h-\tau} (y_{\tau+h}^{h} - \widehat{y}_{i,\tau+h|\tau}^{h})^2, \tag{4.4}$$

where $\delta = 0.90$ and $\kappa = 1, 2$ (see also Stock and Watson (2008b)). Although we focus on $\delta = 0.9$, we also considered the discount factors of $\delta = 1$ and 0.95 but those discount rates did not yield any further gains.[18]

Operationally, we proceed as follows. We compute forecasts based on six families of models with single predictors based on (1) daily and aggregated/quarterly financial assets and (2) daily and aggregated/quarterly financial factors. The term aggregated refers to averaging daily values over the quarter. In each case we estimate two families of MIDAS regression models without leads using daily data (ADL-MIDAS ($J_X = 0$) and FADL-MIDAS ($J_X = 0$)) as well as the corresponding traditional models using aggregated data (ADL and FADL). We also estimate two families of MIDAS regression models with leads (ADL-MIDAS ($J_X = 2$) and FADL-MIDAS ($J_X = 2$)). More precisely, we proceed in three steps. First, for a given family of models and a given asset we compute forecasts using several models with alternative lag structures based on a both fixed lag length scheme and AIC based criterion. Second, for each asset we select the best model specification in terms of its out-of sample performance. And third, given a family of models we deal with uncertainty with respect to the predictors by combining forecasts from models with alternative assets or financial factors.[19]

[18] 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. For robustness purposes we also report in a the online Appendix (see Andreou, Ghysels, and Kourtellos (2010b)) other forecast combination methods including the Mean and the Median, DMSFE (where $\kappa = 1$ and $\delta = 0.9$), Recently Best, Best, and Mallows Model Averaging (MMA). 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. 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. Finally, MMA is an information based method that chooses weights by minimizing the Mallows criterion, which is an approximately unbiased estimator of the MSE and MSFE; see Hansen (2008). Although Bayesian Model Averaging (BMA) has been successful in other studies such as Avramov (2002), Stock and Watson (2006), and Wright (2008), it did not provide any fruitful results in our empirical exercise. One reason is that the combining weights for this approach were highly unstable over time, which may reflect the fact that this method heavily relies in the in-sample fit during an unstable period; see Rapach, Strauss, and Zhou (2009) for a similar finding.

[19] An alternative strategy is to skip the second step and combine forecasts based on a large pool of models assets/factors with alternative lagged structured. One problem with such a strategy is that the forecast combination weights do not have a clear interpretation. We also find that this alternative strategy yields less accurate forecasts. Results based on this alternative strategy are available upon request.

5 Empirical results

Using a recursive estimation method we provide pseudo out-of-sample forecasts (see also for instance, Stock and Watson (2002b) and Stock and Watson (2003)) to evaluate the predictive ability of our models for various forecasting horizons $h = 1$, 2, and 4.[20] The total sample size, $T + h$, is split into the period used to estimate the models, and the period used for evaluating the forecasts. The estimation periods for the 1999 and 1986 samples are 1999:Q1 to 2005:Q4 and 1986:Q1 to 2000:Q4 while the forecasting periods 2006:Q1 + h to 2008:Q4 - h and 2001:Q1 + h to 2008:Q4 - h, respectively. For the 1986 sample we choose to have a longer evaluation period that starts in 2001 (marked by the period after the technology bubble) and for which we can apply asymptotic inference for evaluating predictive gains.

We assess the forecast accuracy of each model using the root mean squared forecast error (RMSFE). For each model we obtain the RMSFE as follows:

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

where $t = T_1, \ldots, T_2$. T_0 is the point at which the first individual pseudo out-of sample forecast is computed. For the sample of 1999 $T_0 = 2006 : Q1$ while for the sample of 1986, $T_0 = 2001 : Q1$. $T_1 = 2006 : Q1 + h$ in the short sample whereas $T_1 = 2001 : Q1 + h$ in the long sample, and $T_2 = 2008 : Q4 - h$ for both sample periods.

The boxplots in the Introduction displayed the RMSE of FADL and FADL-MIDAS without leads ($J_X = 0$) and with leads ($J_X = 2$). A complete representation of the cross-sectional distributions of ADL, FADL, ADL-MIDAS as well as the FADL and FADL-MIDAS models appears in Figure B1 in Andreou, Ghysels, and Kourtellos (2010b). The boxplots represent for each daily asset or factor the RMSFE of 2DiscMSFE forecast combinations for various lag specification such that a single RMSFE is attached to each predictor. We will report in this section the performance of the forecast combinations of these cross-sectional distributions.

We start with a summary of the main empirical findings for forecasting US real economic activity in subsection 5.1. Subsections 5.2 and 5.4 discuss in detail the gains in forecasting real GDP growth from using daily financial predictors and daily financial factors, respectively, as well as the particular classes of financial assets that drive the forecasting gains. Subsection

[20] Due to sample limitations we do not use a rolling forecasting method.

5.3 contains the forecast evaluations via formal forecasting tests. Finally, in subsection 5.5 we compare our results with professional forecasters survey data.

5.1 Main findings

We present the main findings of the paper in Tables 2 through 6 and Figures 5 through 9. These tables report 2DiscMSFE forecast combinations of models using the alternative financial assets or financial factors discussed in section 4.2, thereby addressing uncertainty with respect to the choice of predictors. These results are based on a large number of daily/aggregated assets marked by the data availability in two sample periods (1999 and 1986) as well as daily/aggregated financial factors for the sample of 1999. As noted before, we present evidence for three forecasting horizons, $h = 1$, 2, and 4, quarters ahead forecasts.

In synthesizing the main findings of the paper related to forecasting real US real GDP growth we address the following questions.

(i) *Using reduced-form MIDAS regressions, do financial assets help improve quarterly forecasts of real US GDP?*

Yes, the evidence shows that all four families of MIDAS regression models provide strong forecast gains against the benchmark of RW since their relative RMSFE is, in most cases, substantially below one. Furthermore, MIDAS regression models improve forecasts compared to traditional AR and FAR models as well as to the mean and median forecasts from the Survey of Professional Forecasts (SPF). These findings hold for all forecast horizons, both samples, and for both daily financial assets and daily financial factors.[21]

We should also make two remarks. First, note that quarterly (real) macroeconomic factors play a major role in forecasting quarterly real GDP growth for both MIDAS and traditional models. In particular, forecast combinations that condition on quarterly factors, namely, FADL and FADL-MIDAS($J_X = 0$) provide substantial improvements against the corresponding models ADL and ADL-MIDAS($J_X = 0$). This evidence is consistent with Stock and Watson (2002b) who while they work with a different sample

[21] There is only one notable exception, which concerns forecast combinations of assets in the FX class for the sample of 1999, especially for $h = 4$. Note, however that this negative result is not limited to MIDAS regression models using daily assets but also carries over to traditional models based on aggregated FX series.

period, namely 1959-1998, also find that models using a small number of factors can provide dramatic forecasting gains over benchmark forecasts. Second, in contrast to the existing mixed empirical evidence (Stock and Watson (2003) and Forni, Hallin, Lippi, and Reichlin (2003)), we find that financial assets indeed provide predictive gains on top of real macroeconomic factors. This finding is not limited to MIDAS models but it is evident if one compares all FADL-type models with the corresponding quarterly real factor FAR models. Furthermore, this result is robust whether we use the traditional quarterly aggregated financial assets, but it is stronger and significant when we use the daily frequency of financial assets and our daily financial factors via FADL-MIDAS models. Finally, the gains of FADL-MIDAS models are robust to the two samples of 1999 and 1986 and corresponding evaluation periods of 2006-2008 as well as subsets of financial assets.

(ii) *Is there any predictive role for the daily financial factors beyond the quarterly macroeconomic factors?*

Yes, we find that forecast combinations of FADL-MIDAS ($J_X = 0$) with a single daily financial factor perform better than the corresponding FADL that use quarterly financial factors. In addition, combinations of either of these models have lower RMSFEs than the traditional FAR models which ignore financial factors and are based on quarterly factors extracted mainly from macro variables. This finding holds for all horizons and both sets of financial factors (F_{ALL} and F_{CLASS}). This evidence implies that financial factors can provide forecasting gains beyond those based solely on the quarterly macroeconomic factors, especially when their daily information used in MIDAS regression models. These gains become even stronger when MIDAS regressions use daily financial information with leads.

(iii) *Does daily financial information used in reduced-form MIDAS regressions (without leads) help us improve traditional forecasts using aggregated data?*

Yes, in general, MIDAS regressions without leads (ADL-MIDAS ($J_X = 0$)) and FADL-MIDAS ($J_X = 0$)) can efficiently aggregate daily information to improve traditional forecasts of standard ADL and FADL models that use aggregate data, especially for $h = 1$, and 2, i.e. short horizons. This implies that it is not only the information content of the financial assets or financial factors per se that plays a significant role for forecasting real GDP growth but also the flexible data-driven weighting scheme used by MIDAS regressions.

(iv) *Can MIDAS regressions exploit the daily flow of information to provide more accurate forecasts?*

Yes, overall FADL-MIDAS regression models with leads (FADL-MIDAS ($J_X = 2$)) provide the highest forecast gains, especially when we combine the 25 daily financial factors, F_{CLASS}. In the case of the daily assets, we obtain similar findings, mainly for $h = 1$ and 4, albeit weaker forecast gains in the sample of 1986 relative to the 1999 sample. This finding holds for the entire out-of sample period. While on average the predictive ability of all three families worsens substantially following the financial crisis, the FADL-MIDAS model and in particular the one with leads does not suffer as much losses as the traditional models.

(v) *Which class of financial assets/factors generates the most gains?*

Focusing on the MIDAS regression models with leads that yield the highest forecasting gains, we find that the gains are mainly driven by the classes of Corporate Risk and Equities for both assets and factors. This result appears to be stronger during the 1999 sample for $h = 1$ and 4 relative to that of 1986. More importantly, the Equity assets and their factors not only appear to be stable over the two sample periods but they consistently outperform in RMSFE terms the rest of the asset classes over various sample periods, forecasting periods as well as horizons. Furthermore, for the 1999 sample and $h = 1$ we find that the classes of Government Securities and Corporate Risk systematically provide the highest predictive accuracy. For $h = 1$ in the recent sample Equities is close but overall can be viewed as the third most important class.

5.2 Daily financial assets and factors

In this section we discuss in more detail the forecasting performance of various families of models and different sets of daily predictors for forecasting quarterly US real GDP growth rate. We start with Table 2, which presents RMSFEs for 2DiscMSFE forecast combinations for 8 families of models relative to the RW benchmark. In particular, Panel A of Table 2 reports the relative RMSFEs of AR and quarterly FAR models. Panel B reports models with financial predictors starting with the traditional ADL models and quarterly factor ADL (FADL) models with quarterly/aggregated financial assets or financial factors as well as the corresponding MIDAS models with daily financial assets or factors, namely, the ADL-MIDAS and FADL-MIDAS models without leads ($J_X = 0$) and with leads ($J_X = 2$). The results are grouped into the 1999 and 1986 samples which correspond to RMSFEs combinations for 93 and 65 assets, respectively. For the 1999 sample we consider combinations of the first 5 financial factors based on all 988 daily assets, F^D_{ALL}, as well as the 25 daily factors, F^D_{CLASS}, which include the first 5 factors from each class, namely, F^D_{COMM}, F^D_{CORP}, F^D_{EQUIT}, F^D_{FX}, and F^D_{GOV}.

We find that in most cases it is the leads information in FADL-MIDAS models that yields the highest gains. For both short and long forecasting horizons, $h = 1$ and 4, combinations of these models with the 25 daily financial factors extracted from the five homogeneous classes yield gains of around 48% and 41% vis-à-vis the RW, and 34% to 57% vis-à-vis the quarterly FARs, respectively. Similar gains are obtained from the set of 93 assets especially for $h = 1$ and 4. Notably, for $h = 1$, FADL-MIDAS with leads with the 93 assets yield forecast gains of around 47% vis-à-vis the RW and 36% gains vis-à-vis the combinations of traditional quarterly FAR models. For the longer forecast horizons of $h = 4$, the performance of FADL-MIDAS with leads based on the 93 assets improves over the RW and especially over the ARs and FARs combinations with relative gains of 43%, 63% and 55%, respectively.

Comparing the above results with those obtained for the longer sample of 1986 and the subset of 65 assets, we still find that FADL-MIDAS models with leads yield the highest gains, which are, however, relatively smaller compared to those of the 1999 sample. In our longer sample these models provide 16% and 27% gains over the FAR models, for $h = 1$ and 4, respectively. Similarly, the gains of FADL-MIDAS regression models with leads over the RW and AR benchmarks are around 30% for $h = 1$ and 4. In order to answer the question as to whether the gains in the more recent sample are due to the additional 28 predictors (not available in the 1986 sample) we report the results for the 65 predictors in the 1999 sample and compare them with those for the 93 predictors. We find that in the 1999 sample for $h =$ 1 and 2 the gains of FADL-MIDAS models with leads vis-à-vis the RW, AR and FAR models are similar across the three subsets of daily assets. However, for $h = 4$ it is the combination of the set of 93 daily assets followed by the 25 daily factors in FADL-MIDAS with and without leads that provide the highest forecasting gains. Therefore, while in 1999 the gains for short forecasting horizons are robust in all subsets of assets, it is for longer forecasting horizons that the additional 28 assets help improve the real GDP growth forecasts.

Summarizing we find that forecast combinations of FADL-MIDAS regression models with leads for both the daily financial assets and the 25 daily factors substantially improve over traditional models and benchmarks (RW, AR, FAR, ADL, and FADL). This gains are higher the 1999 sample.

We now turn to compare the RMSFEs of FADL-MIDAS without leads ($J_X = 0$) with the traditional FADL models and those with leads ($J_X = 2$) in order to assess not only the incremental value of daily information but also of the information of daily leads. For $h = 1$ the FADL-MIDAS models with leads provide higher gains than the corresponding model without leads. This finding is consistent for both daily assets and daily financial factors. For instance, for the 1999 sample and $h = 1$ the combinations of FADL-MIDAS with leads using the 93 daily predictors, the 25 daily homogeneous factors and the 5 daily financial factors provide 18%, 11% and 30% gains, respectively, vis-à-vis the corresponding FADL-MIDAS without leads. More importantly, in the 1999 sample for $h = 4$ the FADL-MIDAS with leads deliver gains of up to 41% relative to the corresponding models without leads for combinations of 25 daily financial factors. In the 1986 sample the gains from using daily leads of 65 predictors drop to 16%. Hence the gains of FADL-MIDAS regression models with leads for the 25 daily factors are large for all h compared to FADL-MIDAS regression models without leads and even larger relative to traditional FADL models. Although for the 1999 sample and for $h = 1$ and 2 the RMSFEs of FADL-MIDAS models with leads are similar across the three cross-sections of 93 predictors, 5 and 25 daily factors, it is interesting that for $h = 4$ only the 25 daily factors provide substantial gains in terms of RMSFEs vis-à-vis the FADL as well as FADL-MIDAS models without leads.

We also compare traditional FADL models with FADL-MIDAS regression models without leads and find that in both sample periods (1986 and 1999) and short-run forecasting horizons of $h = 1$ and 2 the MIDAS regression models always outperform the corresponding FADL models in terms of RMSFE. Although the gains from comparing the combinations of these two families of models do not appear to be substantial, in general, this is not the case for the subset of 93 daily predictors since we find 8% gains at $h = 1$ and 11% at $h = 4$, respectively. These results show that there is predictive gain in adopting a MIDAS data-driven aggregation scheme vis-à-vis the flat aggregation scheme in the traditional FADL models for the 93 daily predictors or 25 daily factors. The relative gains are obviously smaller in MIDAS regression models without leads vis-à-vis the FADL models, they are nevertheless evident in short forecast horizons and across both 93 predictors and 25 factors.

Figures 5 and 6 provide recursive time plots of RMSFEs relative to the RW and combinations weights over the evaluation period of 2006-2008. These recursive relative RMSFEs show the forecasting gains of MIDAS models throughout the evaluation period 2006-2008 and 2001-

2008. Figures 5(a)-(c) compare RMSFEs based on FADL and FADL-MIDAS models with ($J_X = 0$) and ($J_X = 2$) for the 1999 sample with 93 daily predictors and the 1986 sample with 63 predictors for $h = 1$ and $h = 4$. Figure 5(a) shows that on average (and ignoring the first few quarters due to the recursive nature of forecasts) the predictive ability of all three families of models is about the same but worsens substantially during the last quarter of 2008, which follows the Lehman Brothers' collapse. Interestingly, the FADL-MIDAS model and in particular the one with leads does not suffer as much losses as the traditional model and as result we are able to obtain the substantial forecasting gains reported in Table 2. In addition, Figures 5(b)-(c) show the gains of FADL-MIDAS ($J_X = 2$) models are not limited in the last quarter but rather they are persistent and substantial, especially for $h = 4$.[22]

Figure 6 shows the recursive time plots of RMSFEs relative to the RW for the forecast combinations of the five daily factors, F^D_{ALL}. In contrast to Figure 5(a), we see that FADL-MIDAS with leads improve forecasts based on the traditional model at all points of time in the evaluation period. At the same point we should note that while the MIDAS without leads improves FADL forecast during the 2007, its predictive ability deteriorates to the level of FADL by the end of 2008. Figure 6(b) and (c) present the time plots for the relative RMSFEs for all 5 daily factors and combination weights, respectively. Ignoring the first few quarters the combination weights appear rather stable. On average $F^D_{ALL,1}$ and $F^D_{ALL,1}$ perform the best.

Overall we find that FADL-MIDAS regression models, provide forecasting gains that are driven not only from the daily frequency of financial assets but mainly from the daily leads which are robust at most points of time in our evaluation period, to different sample periods and different subsets of daily assets and daily financial factors.

5.3 Forecast evaluations

We now turn to evaluate the forecasting evidence presented above. In the 1986 sample we present time-series statistical inference using a number of different tests. However, for the 1999 sample, given the short-time series, we focus on cross-sectional testing in the spirit of Granger and Huang (1997). Appendix A provides a detailed description of the tests.

[22] We also note a sudden drop, mainly in the case of $h = 1$, in the forecasting ability of all the models in the beginning of 2003. Then their performance appears to improve until the recent financial crisis, where we see that their predictive ability deteriorates again.

For the sample of 1986, we use one-sided Diebold and Mariano (1995) tests (DM), Wilcoxon signed rank (W) tests, and Giacomini and White (2006) (GW) tests to evaluate the hypothesis of equal forecasting accuracy between the traditional forecasting regression models based on flat temporal aggregation and the MIDAS regression models (e.g. FADL-MIDAS vs. FADL). The first two tests ignore the effect of estimation uncertainty on relative forecast performance and view this comparison as non-nested. The non-nested structure can be justified since the forecasts are based on forecast combinations across a large number of assets, which involves models with very different lag structures.[23] To deal with both problems we also employ the GW test, which accounts for estimation uncertainty and is valid for both nested and non-nested hypotheses. For the comparisons of the six family of models (ADL, FADL, ADL-MIDAS, FADL-MIDAS without leads and with leads) against the RW we employ the Clark and West (2007) (CW), which is an adjusted version of the Diebold and Mariano (1995) statistic. For the sample of 1999, we employ two cross-sectional statistics of equal predictive ability. The first one is based on the difference in MSFE for each asset. Then we test for zero mean, median, and top quartile of the cross-sectional distribution of this statistic. We report the p-values based on the asymptotic critical values.[24] Similarly, the second cross-sectional test is based on the standardized difference in MSFE, which is the DM for each asset. The advantage of the latter is that it takes into account the uncertainty from the time-series dimension.

Table 4, presents the equal forecasting accuracy test of CW in Panel A along with the DM, W, GW in Panel B for the sample of 1986.[25] Panel A tests whether 2DiscMSFE forecast combinations for the 6 families of models yield significant results against forecasts based on the RW. More precisely, we find that FADL-MIDAS ($J_X = 2$) yields significantly lower MSFE than the MSFE of the RW for all forecasting horizons at 10% size of the test. In the case of no leads we find that significant results only for $h = 1$, 2. Interestingly, the only significant result for traditional models based on aggregated daily data is limited to FADL model in the case of $h = 1$. Panel B provides the equal forecasting accuracy test of DM and W that test for equal forecasting accuracy between forecast combinations of MIDAS

[23]Recall that for each asset we choose the best model in terms of RMSFE over different lag structures

[24]Similar results are obtained when the distribution of the statistics is bootstrapped with replacement from the asset based empirical distribution.

[25]For DM, CW, and GW statistics, we always report results based on the sample variance, even for multi-step forecasts. Given the small sample size we expect that these estimates are more accurate than estimates based on HAC, albeit the serial correlation problem. Results based on HAC are qualitatively similar and available upon request.

regression models vis-à-vis those obtained from traditional model. In general we find that MIDAS regression models yield significant gains over the traditional models. In particular, the results are strongest for MIDAS with leads - both ADL-MIDAS ($J_X = 2$) and FADL-MIDAS ($J_X = 2$)) appear significant for all horizons. The results for GW are a bit weaker, especially for $h = 1$ but nevertheless significant for at least $h = 1, 2$ and the models that include quarterly factors. Table 5 presents the cross-sectional tests for predictive ability for sample of 1999. In general we find that the forecast gains of MIDAS regression models against the traditional models are significant, especially in the case of $h = 1$ and top quartile.

5.4 Classes of assets

We now look deeper into our cross-section in order to identify if certain classes of financial assets drive the forecasting gains of US real GDP growth rate. In Table 3 we compare the relative RSMFEs of forecast combinations from all assets vis-à-vis those obtained from each of the 5 classes of assets. Panel A reports the results for the 1999 sample for the 93 daily assets and 25 daily factors. Panel B reports the corresponding results for the 1986 sample based on the 65 daily assets.

In the 1999 sample we find that combinations of FADL-MIDAS regression models with leads for both $h = 1$ and 4 present the highest forecasting gains using either the 93 daily predictors or the 25 daily factors, reported in the first three columns of the table. The driving forces for these gains are the predictors in two classes of daily assets or factors: Corporate risk, Equities and Government securities. In particular, the highest gains are obtained from combinations of Corporate risk assets and factors using FADL-MIDAS with leads in forecasting real GDP growth especially for $h = 4$. Similar, albeit weaker, results are obtained for the 1986 sample. Interestingly, the classes of Equities and Corporate risk alone can provide gains that encompass forecasts combinations across all 5 classes of asset; see the online Appendix Table B4

Next, we investigate the time-series plots of the relative RMSFEs of the five classes (see Figure 7) and their combination weights (see Figure 8) focusing on FADL-MIDAS ($J_X = 2$).[26] For the 1999 sample and $h = 1$ we find that the Government Securities and Corporate Risk assets systematically provide the highest predictive accuracy throughout our forecasting

[26] To obtain these combination weights we first obtain forecast combinations for each class of asset. Then, we apply forecast combinations again across the 5 combined forecasts to obtain the combination weights.

period. Equities are close but overall can be viewed as the third most important class in this case. More importantly, the forecasting power of Corporate risk assets appears to be the least affected by the Lehman Brothers' fallout in the last quarter of 2008 and hence this class is singled out as the best performing class of predictors in the Table 3. This result holds for both the 1999 and 1986 samples when h=1 and is particularly strong at the end of the forecasting period as shown by the largest relative weight given to the corporate risk series (see the first two Figures in 8)). However, for $h = 4$ in the 1986 sample we find that Equities is by far the best performing class of assets. In fact Equities exhibit the highest gains during the 2004-2006 period but then suffers a sudden loss of predictive ability which is also apparent in the combination weights (shown in the last Figure of (see Figures 7 and 8), respectively). Nevertheless, Equities appear to provide strong gains throughout the forecasting period and even even during the recent financial crisis. It is also worth noting that the Equities class has very similar assets in the two sample periods and is especially useful for forecasting in the long horizons. Figure 9 repeats the analysis for the daily financial factors of the five classes of assets in the case of $h = 1$. The plots show that forecast combinations of daily factors extracted from the class of Corporate risk provide overall the highest gains throughout the forecasting period followed by the Government securities. This result is robust to both the daily predictors and daily factors in these two classes. However, at the end of the evaluation period marked by the financial crisis, the small set of daily corporate risk and fixed income assets performs better than the corresponding daily factors.

Within the best performing classes of assets of Corporate risk, Equity, and Government securities we identify the set of best predictors found in the top 10 percentile of the RMSFEs distributions of the cross-section of assets for both $h = 1$ and 4. Given that a large body of literature has proposed different assets as important predictors for economic activity, it is also interesting to evaluate the stability of such predictors in the two samples of 1986 and 1999; see Table 6. Note that in the Equities class the 9 assets that appear in the top quartile are similar in the two sample periods. For example in 1986, the S&P500 returns, excess S&P500 returns and futures, the standardized S&P500 returns by VIX or VXO, and Nasdaq returns as well as the SMB and UMD Fama-French factors provide the highest forecasting gains in both $h = 1$ and 4. This result is consistent in the shorter sample of 1999 for $h = 4$. In the Corporate risk class the set of best predictors in 1999 for $h = 4$ are the 1 month Eurodollar spread (1MEuro-FF), the A2F2P2 commercial paper spreads (APFNF-AAF and APFNF-AANF) and some of the Moody's Corporate risk spreads. Moreover, it is worth mentioning that in addition to Equities and Corporate risk, the Breakeven inflation predictors (and especially BEIR1F4) as well as the Canadian vis-a-vis the US dollar are among the set of best predictors only for short forecasting horizons ($h = 1$) in 1999. For the Government securities we also find that the 10 year bond yield and the six months interest rates spread are among the best predictors for our sample period.

Given this evidence we employ the Giacomini and Rossi (2009) forecast breakdown (FB) test to examine whether the out-of sample performance of the forecast model is significantly worse than its in-sample performance. We apply this test for the 1986 period given the longest time-series of RMSFEs available. The FB test examines whether the out-of sample performance of the forecast model is significantly worse than its in-sample performance in the sample of 1986. Focusing on the best performing models of FADL-MIDAS with leads reported in Table 6 we find that we always accept the null of no forecast breakdown.[27] Hence the forecasts based on the assets in the top quartile of the distribution of all classes of using FADL-MIDAS models with leads are stable during this period. Another interesting result from comparing the RMSFEs of the best performing models in 6 and those obtained from combinations of the classes of assets in 3, is that for h=4, the combinations of corporate risk assets perform even better than the best performing daily asset. This also holds for the equity class and h=4 in the 1986 sample. Hence, the prediction gains from forecast combinations.

In concluding we note that the three classes of assets (corporate risk, equity and government securities) that deliver the strongest forecasting gains consist of both traditional predictors considered in the literature as well as some new predictors considered here. The RMSFE forecast gains as well as the consistency of these gains throughout both the 1986 and 1999 samples can be explained by the fact we use the daily information of financial predictors in conjunction with MIDAS models, especially with leads.

5.5 Comparing survey and MIDAS forecasts

In this final subsection we compare MIDAS regression-based forecasts with survey-based ones. The latter are taken from the Survey of Professional Forecasts (SPF) obtained from the website of the Philadelphia Fed.[28] The predictive ability of surveys for inflation has been

[27]This result even holds for the larger set of the best performing daily factors in the top quartile reported in Table B6 appearing in Andreou, Ghysels, and Kourtellos (2010b). The only notable exception is ADS in the case of $h = 1$.

[28]For details see `http://www.philadelphiafed.org/research-and-data/`.

widely documented, especially for Greenbook forecast; see for example Ang, Bekaert, and Wei (2007) and Faust and Wright (2009) who conclude that survey-based measures yield the best results for forecasting CPI Inflation. However, there is mixed evidence for the gains of survey forecasts for US real GDP growth. Faust and Wright (2009) note that the success of the surveys is not extended to forecasting the GDP growth because these surveys cannot offer much gains over an AR(1) forecast.[29]

A comparison with survey data brings us to an important issue about availability of such forecasts. Conducting surveys is costly, and consequently such forecasts are often stale. The infrequent availability of survey forecasts prompted Ghysels and Wright (2009) to suggest to use MIDAS regressions - involving financial series - to anticipate survey forecasts. Ghysels and Wright were concerned with producing survey forecasts on the eve of FOMC meetings. The advantage of MIDAS regression-based forecasts is their availability on a real-time basis, daily, weekly or monthly. The very same issue makes the comparison of MIDAS regression-based forecasts and survey-based ones somewhat more difficult. The SPF forecasts are conducted in the middle of the second month of each quarter. We will therefore compare the SPF forecasts with the forecasts based on MIDAS with leads for which the forecaster stands on the first day of the last month of the quarter. There is a slight difference here that might slightly favor the regression-based approach.[30] We compute the SPF forecasts of the GDP growth using the median and the mean forecast data for levels and denote the forecast for growth in the current quarter by $h = 1$ as we do for forecasts based MIDAS with leads.

The results for the 1986 sample - which allows us to apply formal statistical tests - are reported in Table 7. They show that FADL-MIDAS models with ($J_X = 2$) significantly improve real US GDP growth forecasts compared to the SPFs for one year ahead forecasts, h=4.[31]

At the shorter forecast horizon of $h = 1$, i.e. the nowcasting setting, we learn from Table 7 that the comparison between survey-based and MIDAS regression-based forecasts are statistically insignificantly different. This means that regression-based methods do as well as surveys. Recall, however, that MIDAS regression-based forecasts are readily available on

[29]Unfortunately, we cannot compare our results with Greenbook forecasts since Greenbook data are not publicly available after 2004.

[30]We have also compared MIDAS without leads with survey forecasts - where the advantage tilts towards surveys - and found results similar to those reported here.

[31]In fact for the one-year forecast horizon it appears that SPF forecasts cannot improve upon the RW forecasts. The latter evidence is consistent with the findings of D'Agostino, Surico, and Giannone (2009).

a daily/weekly/monthly basis, as opposed to survey-based ones that are more cumbersome to collect. One could therefore view the equal forecasting performance at the short horizon and the better performance at the longer horizon of MIDAS regression-based forecasts as an important improvement.

6 Conclusion

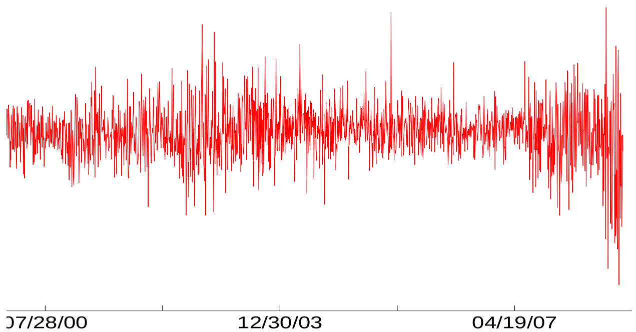
We studied how to incorporate the information in daily financial into forecasting of quarterly real GDP growth. The new methods involve forecast combinations of MIDAS regressions either based in cross-sections of individual series or based on daily factors extracted from large cross-sections of financial data.

We find that MIDAS regression models provide substantial forecast gains against the benchmark of RW and most importantly FADL and FADL-MIDAS($J_X = 0$) provide substantial gains against the corresponding models ADL and ADL-MIDAS($J_X = 0$). Moreover, daily financial factors improve forecasts beyond the quarterly macroeconomic factors. We also find that overall FADL-MIDAS regression models with leads (FADL-MIDAS ($J_X = 2$)) provide the highest forecast gains, especially when we combine the 25 daily financial factors. Focusing on the forecasting gains of MIDAS regression models with leads we find that the gains are mainly driven by the classes of Corporate risk and Equities for both assets and factors. While on average the predictive ability of all three families worsens substantially following the financial crisis, the FADL-MIDAS model and in particular the one with leads does not suffer as much losses as the traditional models.

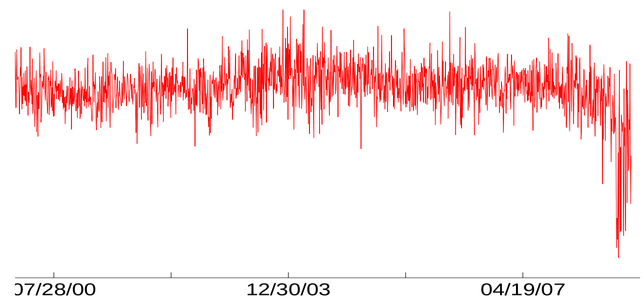
Finally, forecasting of real GDP growth is only one of many examples where our methods apply. The generic question we addressed is how one can use large panels of high frequency data to improve forecasts of low frequency series. There are many other macroeconomic series to which this can be applied. In addition, there are many other practical applications in finance and other fields where this problem occurs. The methods we described are therefore of general interest beyond the specific application consider in the present paper.

Figure 2: The daily factors extracted from *all* daily assets

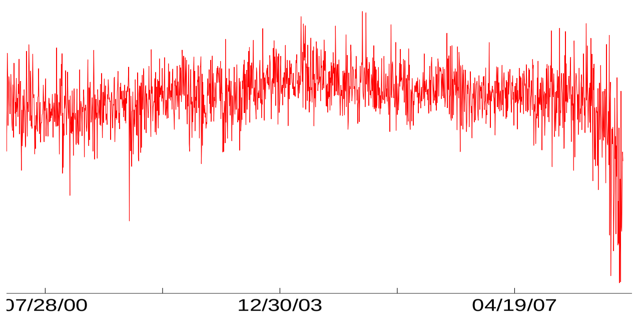
(a) $F_{ALL,1}$



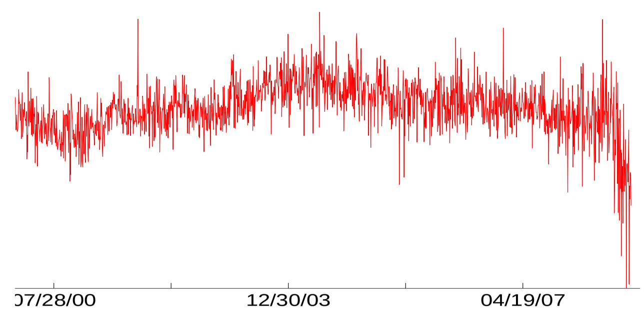
(b) $F_{ALL,2}$



(c) $F_{ALL,3}$



(d) $F_{ALL,4}$



(e) $F_{ALL,5}$

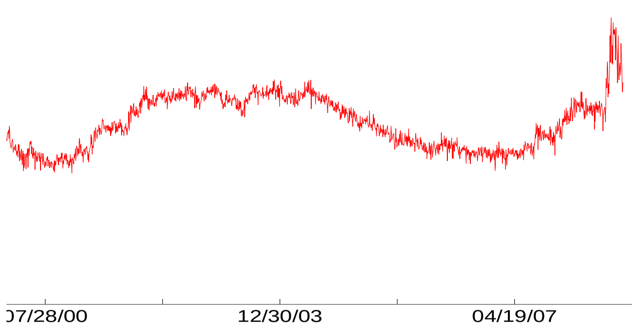
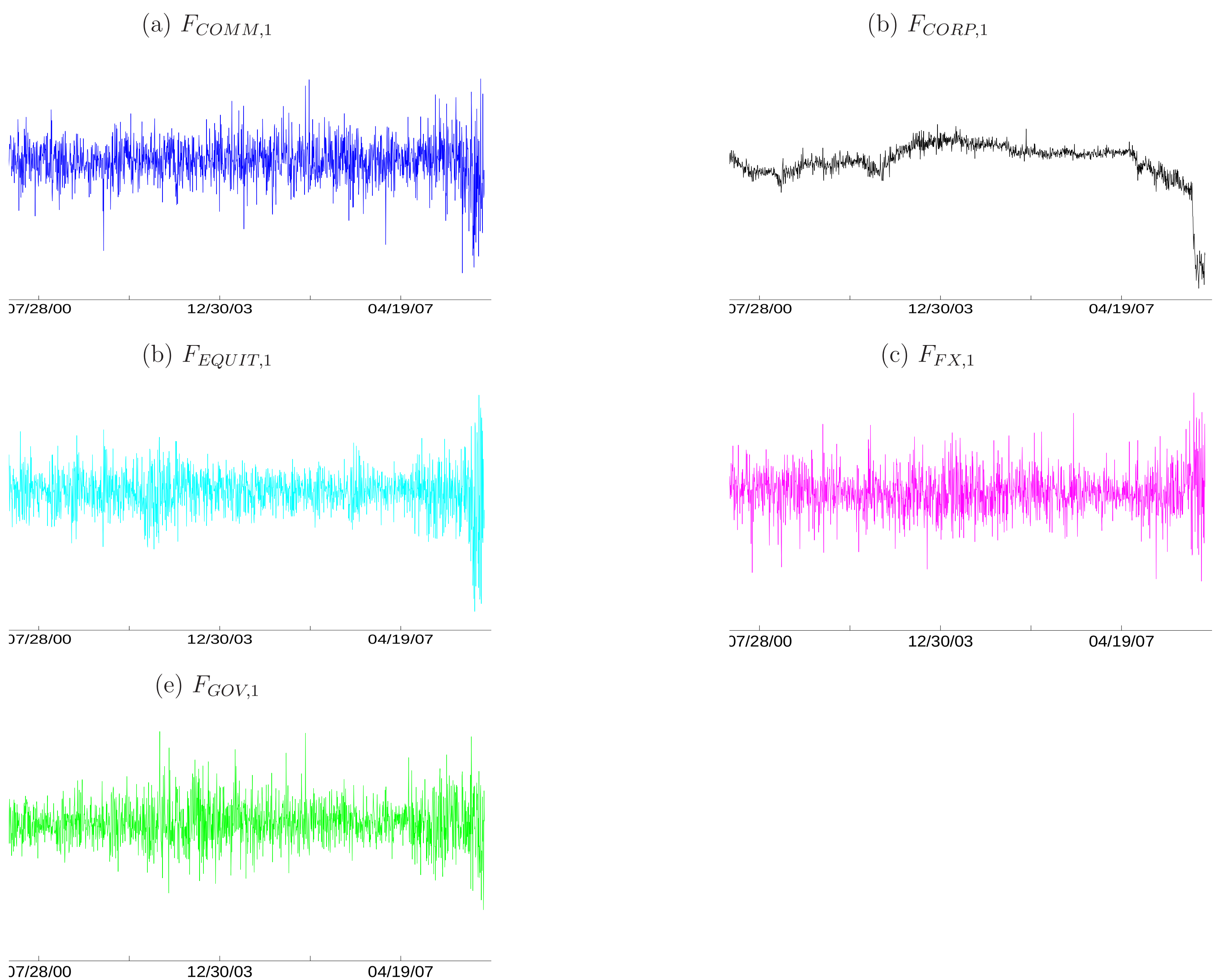


Figure 3: The first daily factors extracted from the 5 classes of assets



(a) $F_{COMM,1}$

(b) $F_{CORP,1}$

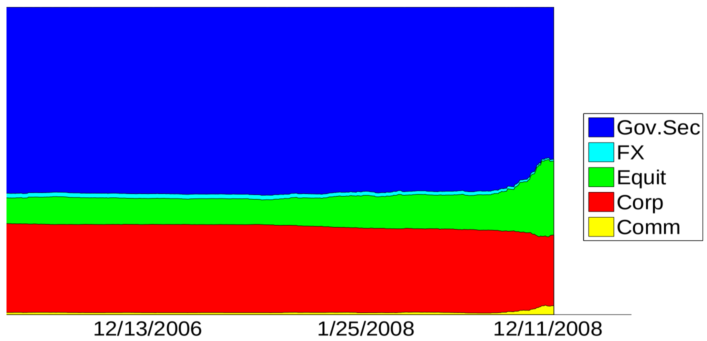
(b) $F_{EQUIT,1}$

(c) $F_{FX,1}$

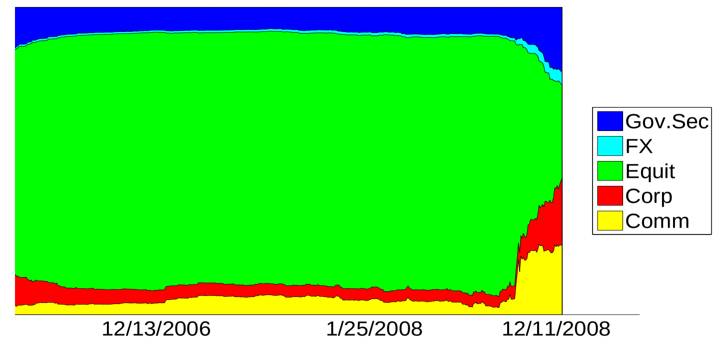
(e) $F_{GOV,1}$

Figure 4: Sum of squared loadings for the daily financial factors extracted from *all* daily assets

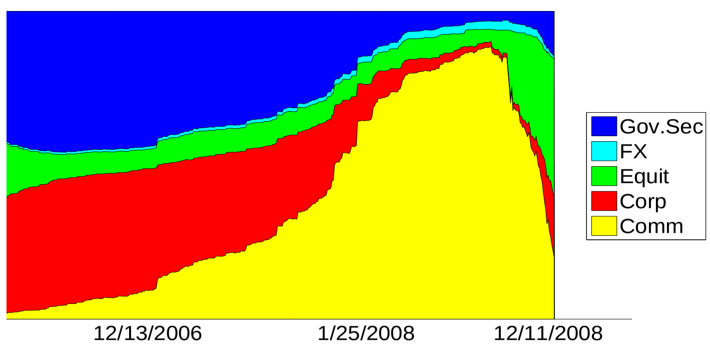
(a) $F_{ALL,1}$



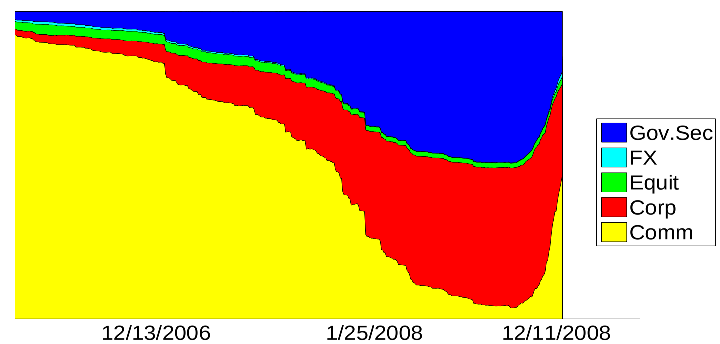
(b) $F_{ALL,2}$



(c) $F_{ALL,3}$



(d) $F_{ALL,4}$



(e) $F_{ALL,5}$

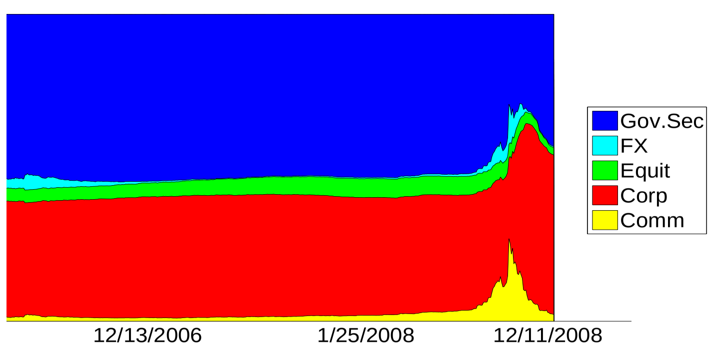
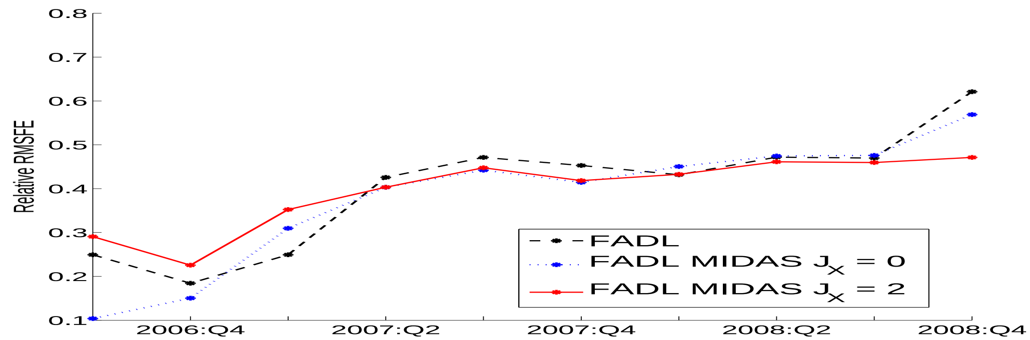
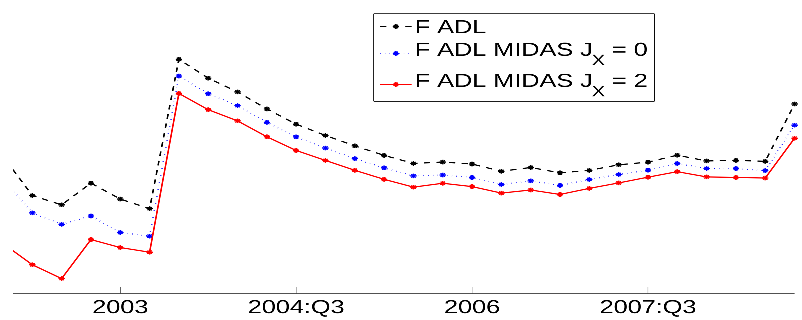


Figure 5: RMSFE of 2DiscMSFE forecast combinations for daily financial assets

(a) Sample of 1999: 93 daily assets, h = 1



(b) Sample of 1986: 65 daily assets, h = 1



(c) Sample of 1986: 65 daily assets, h = 4

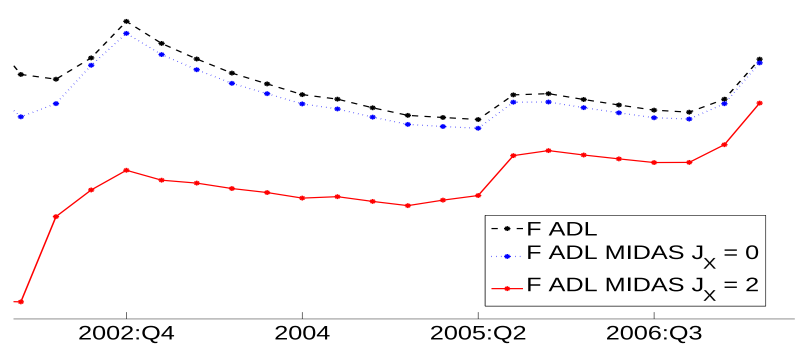
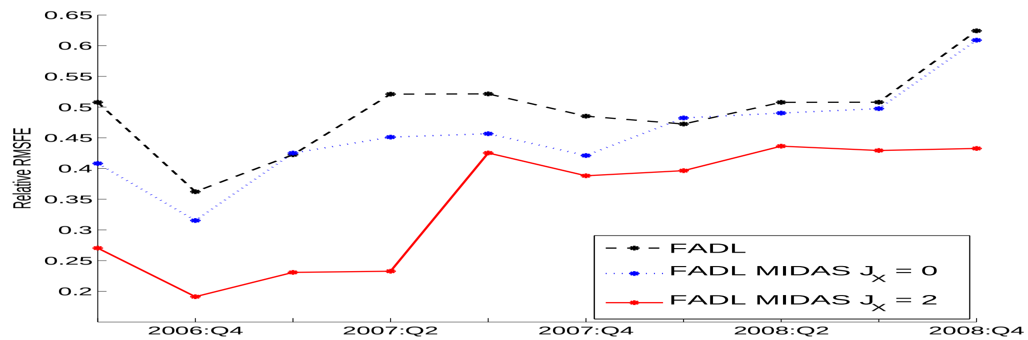
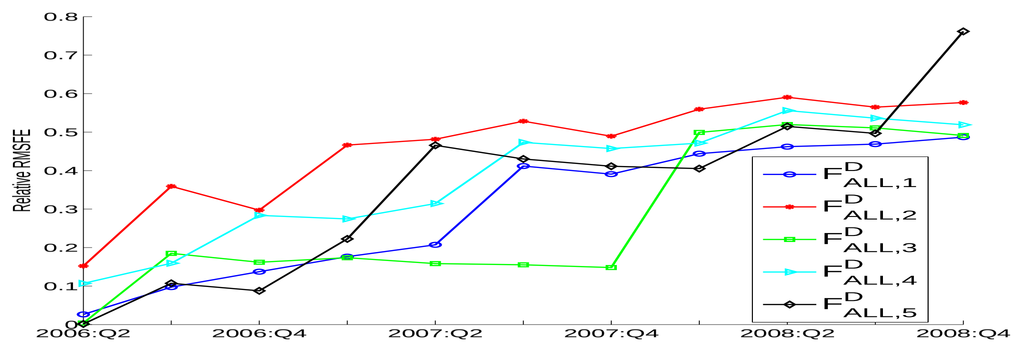


Figure 6: 5 daily financial factors extracted from *all* daily financial assets, ($F_{ALL,j}$, j=1,2,..,5)

(a) RMSFE of 2DiscMSFE forecast combinations, h = 1



(b) RMSFE of FADL-MIDAS ($J_X = 2$), h = 1



(c) 2DiscMSFE combination weights, h = 1

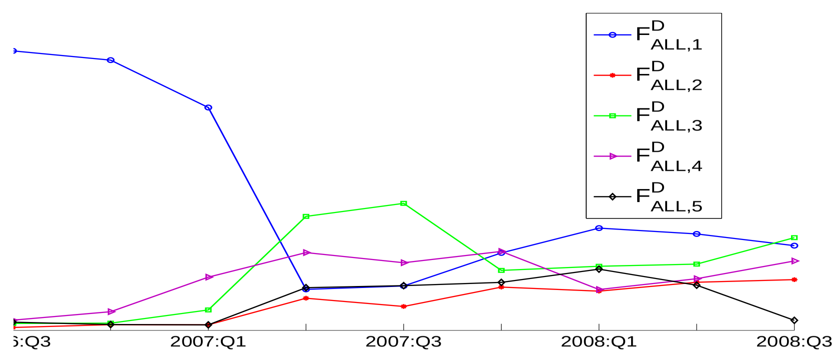
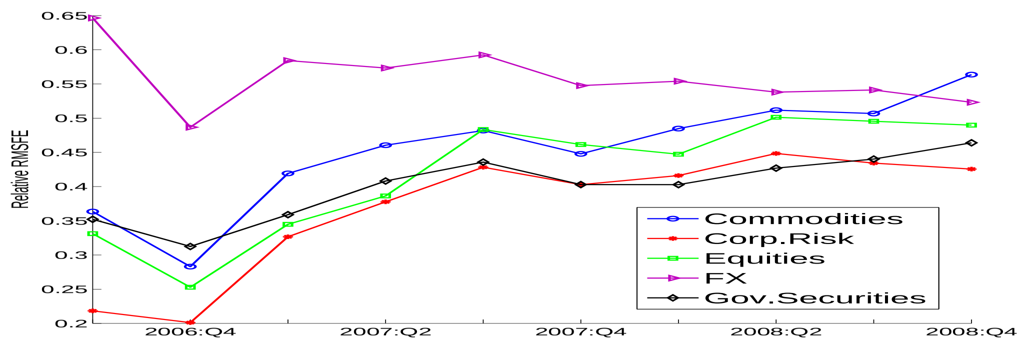
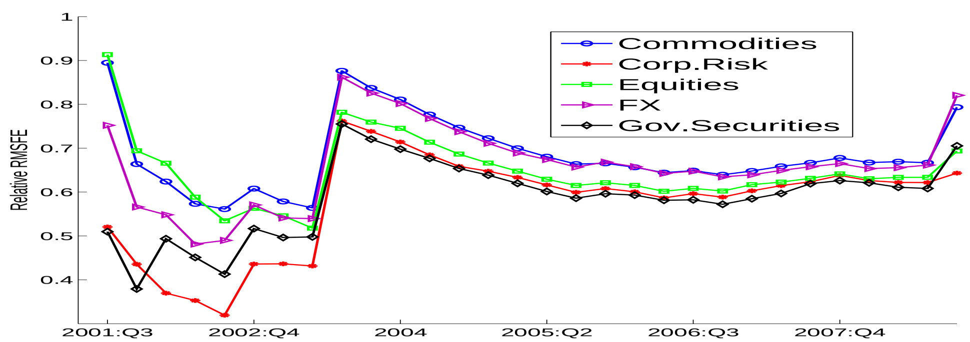


Figure 7: RMSFE of 2DiscMSFE forecast combinations of FADL-MIDAS ($J_X = 2$) for each of the 5 classes of daily financial assets

(a) Sample of 1999: 93 daily assets, h = 1



(b) Sample of 1986: 65 daily assets, h = 1



(c) Sample of 1986: 65 daily assets, h = 4

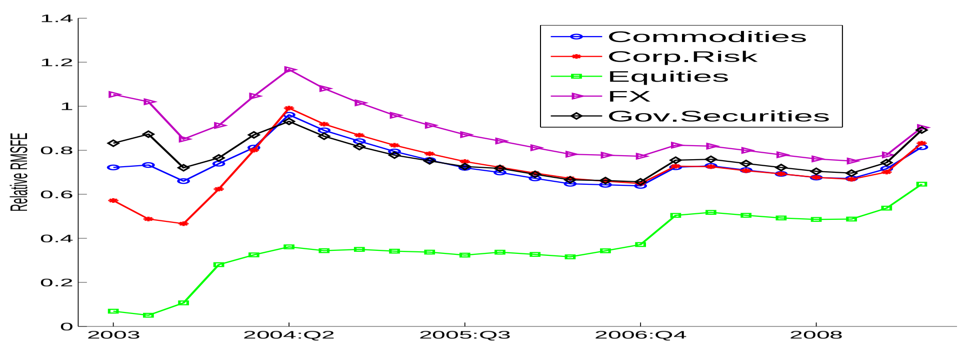
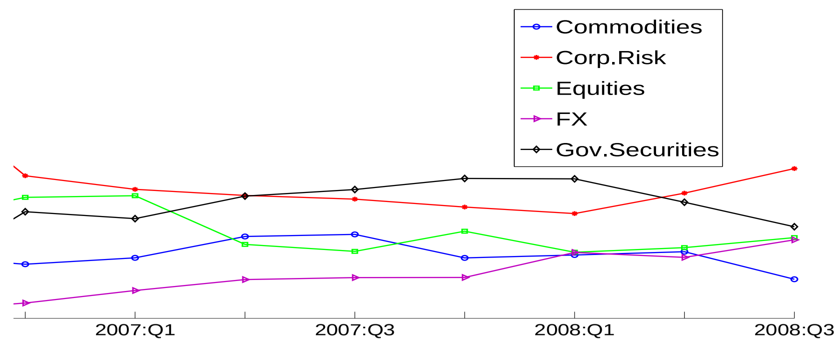
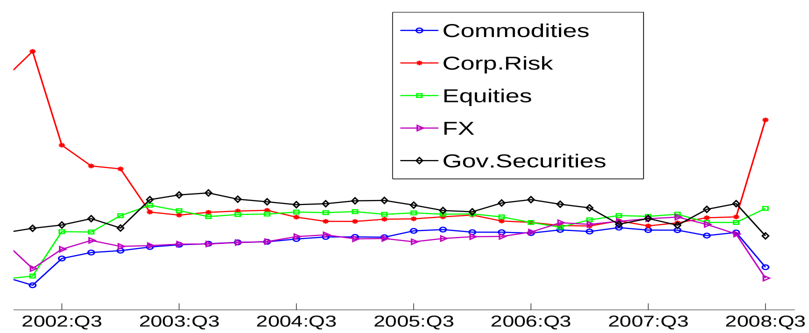


Figure 8: 2DiscMSFE combination weights of FADL-MIDAS ($J_X = 2$) for each of the 5 classes of daily financial assets

(a) Sample of 1999: h = 1



(b) Sample of 1986: h = 1



(c) Sample of 1986: h = 4

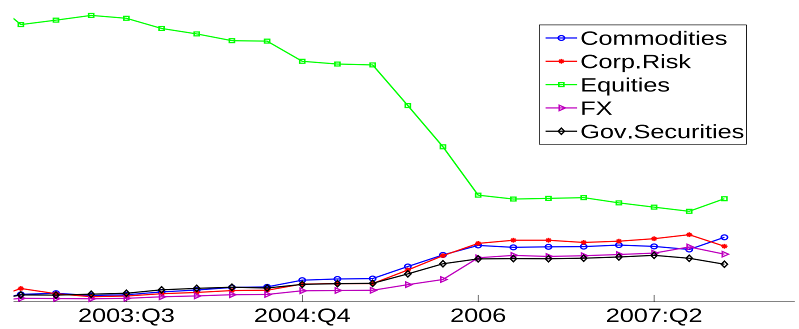
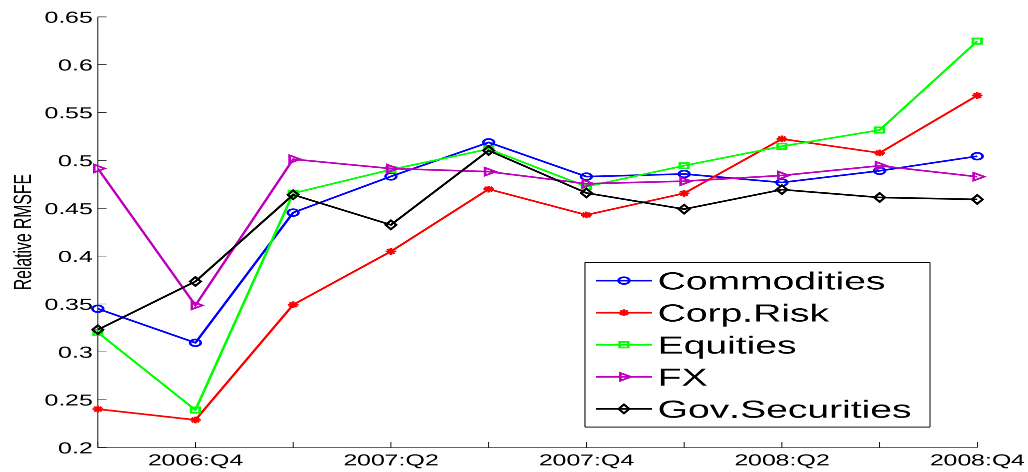


Figure 9: 2DiscMSFE forecast combinations of FADL-MIDAS ($J_X = 2$) for the 5 classes of daily financial factors

(a) RMSFE



(b) Combination weights

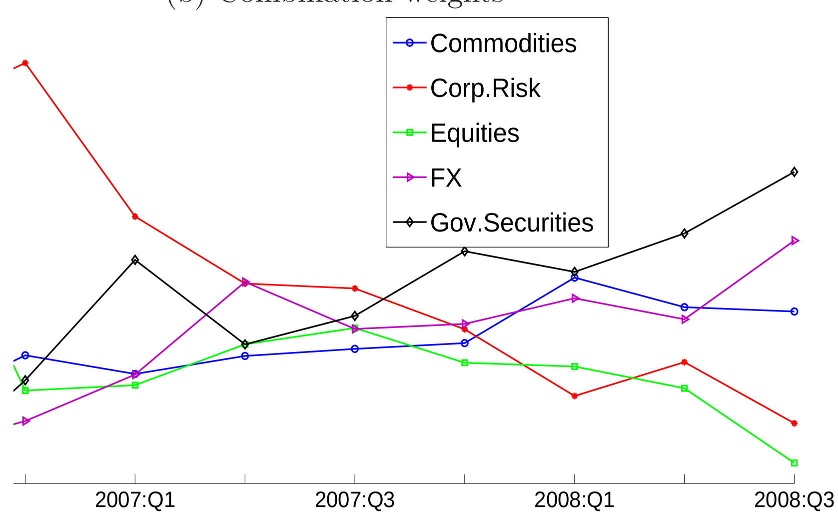


Table 1: Eigenvalues of the daily factors

Daily financial factors are obtained from a Dynamic Factor Model (DFM) with time-varying factor loadings appearing in equation (4.2). The factors are estimated using a principal component method that involves cross-sectional averaging of the individual predictors. Panel A shows the standardized eigenvalues for the whole sample period for 10 daily factors extracted using the cross-section of 988 predictors, F^D_{ALL}, as well as the factors extracted from the 5 categories of financial assets described above: $F_{CLASS} = (F^D_{COMM}, F^D_{CORP}, F^D_{EQUIT}, F^D_{FX}$, and $F^D_{GOV})$. 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 provides the sum of square loadings of $F^D_{ALL,j}$, $j = 1, 2, .., 5$ for the 5 Classes of Assets. The database covers a large cross-section of 988 daily series from 1/1/1999-31/12/2008 (1777 trading days) for five classes of financial assets described in detail in the online Appendix of the paper (see Andreou, Ghysels, and Kourtellos (2010b)).

	Panel A: Eigenvalues of Daily Factors						Panel B: Sum of squared loadings				
	ALL	COMM	CORP	EQUIT	FX	GOV	COMM	CORP	EQUIT	FX	GOV
F_1^D	0.36	0.58	0.39	0.79	0.67	0.55	0.03	0.23	0.24	0.01	049
F_2^D	0.22	0.19	0.34	0.08	0.14	0.19	0.22	0.22	0.30	0.04	0.21
F_3^D	0.18	0.11	0.16	0.06	0.08	0.11	0.20	0.19	0.45	0.01	0.15
F_4^D	0.14	0.06	0.07	0.04	0.06	0.08	0.47	0.30	0.02	0.02	0.20
F_5^D	0.10	0.05	0.04	0.03	0.05	0.07	0.02	0.52	0.02	0.00	0.43

Table 2: RMSFE for 2DiscMSFE forecast combinations

This table presents RMSFEs of 2DiscMSFE forecast combinations for real GDP growth relative to the RMSFE of RW for 1-, 2-, and 4-step ahead forecasts for two sample periods: 1999 and 1986. Panel A includes results on the benchmark models of RW (at absolute values), AR, and FAR as well as for the median and mean SPF forecasts. Panel B includes forecast combination results on 93 daily financial assets for the sample of 1999 as well as a subset of 65 daily predictors for both samples of 1999 and 1986. It also includes forecast combination results on the 5 daily financial factors extracted from all 988 variables and the 25 daily financial factors obtained from the five homogeneous classes of assets (5 from each classes) for the sample of 1999. The estimation periods for the 1999 and 1986 samples are 1999:Q1 to 2005:Q4 and 1986:Q1 to 2000:Q4 while the forecasting periods 2006:Q1 + h to 2008:Q4 - h and 2001:Q1 + h to 2008:Q4 - h, respectively. The Entries below one imply improvements compared to the benchmark.

Panel A: benchmarks

	Sample of 1999			Sample of 1986		
Forecast Horizon	1	2	4	1	2	4
RW	3.35	2.48	1.69	2.56	1.85	1.18
AR	1.00	1.02	1.16	0.96	0.99	1.01
FAR	0.73	0.73	0.95	0.84	0.89	0.96

Panel B: daily assets and daily factors

	Sample of 1999												Sample of 1986		
	93 daily assets			65 daily assets			5 daily factors (F_{ALL})			25 daily factors (F_{CLASS})			65 daily assets		
Forecast Horizon	1	2	4	1	2	4	1	2	4	1	2	4	1	2	4
ADL	0.88	0.80	0.79	0.89	0.88	0.95	0.79	0.74	0.88	0.80	0.76	0.90	0.86	0.92	0.91
FADL	0.62	0.61	0.55	0.62	0.63	0.67	0.62	0.73	0.59	0.58	0.63	0.66	0.77	0.80	0.85
ADL-MIDAS ($J_X = 0$)	0.77	0.75	0.76	0.78	0.83	0.95	0.66	0.73	0.88	0.79	0.74	0.90	0.77	0.89	0.89
FADL-MIDAS ($J_X = 0$)	0.57	0.54	0.40	0.56	0.55	0.62	0.61	0.64	0.94	0.54	0.58	0.69	0.73	0.79	0.83
ADL-MIDAS ($J_X = 2$)	0.62	0.73	0.67	0.67	0.78	0.77	0.41	0.57	0.84	0.66	0.73	0.63	0.76	0.86	0.81
FADL-MIDAS ($J_X = 2$)	0.47	0.57	0.43	0.48	0.60	0.47	0.43	0.56	0.92	0.48	0.53	0.41	0.70	0.76	0.70

Table 3: RMSFE for 2DiscMSFE forecast combinations for blocks of assets

Entries are the Relative RMSFE of Forecast Combinations of daily financial assets and factors based on 2DiscMSFE for various classes of assets, for 1-, 2- and 4-step ahead forecasts, and for two sample periods: 1999 and 1986. The sample of 1999 includes forecast combination results on 93 assets, 5 factors based on 988 variables and 25 factors obtained from five homogeneous blocks of assets (5 from each block). The sample of 1986 includes forecast combination results on 65 daily predictors. The columns under the heading ALL refer to the combination results based on 93 predictors or 25 daily block factors (5 from each block). The five classes of assets are Commodities, Corporate Risk, Equities, Exchange Rates, and Government Securities, respectively. All models are summarized in Table (B3). 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			COMM			CORP			EQUIT			FX			GOVSEC		
Forecast Horizon	1	2	4	1	2	4	1	2	4	1	2	4	1	2	4	1	2	4
										Panel A: sample of 1999								
										daily financial assets								
ADL	0.88	0.80	0.79	0.94	0.92	1.00	0.81	0.64	0.62	0.86	0.83	1.06	0.97	1.00	1.16	0.97	0.94	0.84
ADL-MIDAS ($J_X = 0$)	0.77	0.75	0.76	0.92	0.92	0.89	0.66	0.58	0.67	0.80	0.87	1.07	0.96	0.99	1.15	0.86	0.82	0.88
ADL-MIDAS ($J_X = 2$)	0.62	0.73	0.67	0.90	0.88	1.00	0.56	0.62	0.50	0.54	0.76	0.65	0.86	1.01	1.11	0.67	0.87	0.79
FADL	0.62	0.61	0.55	0.68	0.61	0.73	0.66	0.62	0.36	0.63	0.65	0.62	0.55	0.74	1.07	0.65	0.71	0.69
FADL-MIDAS ($J_X = 0$)	0.57	0.54	0.40	0.59	0.56	0.76	0.63	0.48	0.23	0.58	0.60	0.83	0.57	0.66	1.07	0.60	0.65	0.78
FADL-MIDAS ($J_X = 2$)	0.47	0.57	0.43	0.56	0.58	0.79	0.43	0.50	0.22	0.49	0.64	0.50	0.52	0.72	1.09	0.46	0.67	0.76
										daily financial factors								
ADL	0.80	0.76	0.90	0.96	0.91	0.98	0.71	0.57	0.86	0.94	0.92	0.91	0.75	0.99	0.99	0.96	0.94	0.90
ADL-MIDAS ($J_X = 0$)	0.79	0.74	0.90	0.92	0.86	0.99	0.66	0.59	0.87	0.87	0.88	0.84	0.80	0.99	0.94	0.93	0.91	0.96
ADL-MIDAS ($J_X = 2$)	0.66	0.73	0.63	0.86	0.85	0.66	0.54	0.60	0.43	0.75	0.84	0.93	0.79	0.98	0.98	0.68	0.94	0.82
FADL	0.58	0.63	0.66	0.73	0.71	0.73	0.59	0.54	0.58	0.71	0.68	0.60	0.51	0.69	0.87	0.72	0.76	0.93
FADL-MIDAS ($J_X = 0$)	0.54	0.58	0.69	0.67	0.58	0.89	0.51	0.56	0.58	0.66	0.68	0.61	0.47	0.66	0.85	0.65	0.68	0.95
FADL-MIDAS ($J_X = 2$)	0.48	0.53	0.41	0.50	0.66	0.49	0.57	0.50	0.28	0.62	0.72	0.45	0.48	0.67	0.99	0.46	0.57	0.93
										Panel C: sample of 1986								
										daily financial assets								
ADL	0.86	0.92	0.91	0.92	0.94	0.96	0.83	0.93	0.92	0.84	0.88	0.93	0.93	0.96	0.96	0.92	0.96	0.86
ADL-MIDAS ($J_X = 0$)	0.77	0.89	0.89	0.89	0.92	0.93	0.73	0.93	0.90	0.78	0.84	0.90	0.93	0.95	0.93	0.90	0.94	0.88
ADL-MIDAS ($J_X = 2$)	0.76	0.86	0.81	0.87	0.91	0.87	0.67	0.92	0.88	0.76	0.82	0.74	0.94	0.96	0.92	0.84	0.94	0.88
FADL	0.77	0.80	0.85	0.80	0.81	0.91	0.72	0.79	0.74	0.78	0.79	0.87	0.82	0.87	0.96	0.80	0.87	0.87
FADL-MIDAS ($J_X = 0$)	0.73	0.79	0.83	0.79	0.80	0.85	0.69	0.81	0.83	0.75	0.77	0.85	0.83	0.86	0.91	0.80	0.85	0.89
FADL-MIDAS ($J_X = 2$)	0.70	0.76	0.70	0.79	0.80	0.82	0.64	0.79	0.83	0.69	0.74	0.65	0.82	0.86	0.91	0.70	0.83	0.89

Table 4: Time-series tests for predictive ability for the 1986 sample

This tables presents (i) the Clark-West (CW) for testing whether the difference in the MSFEs of 2DiscMSFE Forecast Combinations and the RW is zero and (ii) and one-sided Diebold-Mariano (DM), Wilcoxon's signed rank, and Giacomini-White (GW) statistics for testing for equal forecasting accuracy between the 2DiscMSFE forecast combinations of MIDAS models against the traditional models.

Panel A: 2DiscMSFE forecast combinations against RW

Forecast Horizon	1		2		4	
	CW	p-val	CW	p-val	CW	p-val
ADL	0.84	0.20	0.64	0.26	0.68	0.25
FADL	1.46	0.07	1.27	0.10	0.95	0.17
ADL-MIDAS ($J_X = 0$)	1.31	0.10	0.81	0.21	0.86	0.19
FADL-MIDAS ($J_X = 0$)	1.69	0.05	1.37	0.09	1.02	0.15
ADL-MIDAS ($J_X = 2$)	1.36	0.09	0.95	0.17	1.25	0.11
FADL-MIDAS ($J_X = 2$)	1.78	0.04	1.40	0.08	1.69	0.05

Panel B: 2DiscMSFE MIDAS forecast combinations against 2DiscMSFE flat forecast combinations

Forecast Horizon	1						2						4					
	DM	p-val	W	p-val	GW	pval	DM	p-val	W	p-val	GW	pval	DM	p-val	W	p-val	GW	pval
ADL vs. ADL-MIDAS ($J_X = 0$)	1.15	0.13	1.78	0.04	3.72	0.16	1.47	0.07	0.87	0.19	3.31	0.19	1.47	0.07	1.71	0.04	2.17	0.34
ADL vs. ADL-MIDAS ($J_X = 2$)	1.41	0.08	1.76	0.04	4.37	0.11	2.12	0.02	2.41	0.01	9.49	0.01	3.20	0.00	3.26	0.00	14.99	0.00
FADL vs. FADL-MIDAS ($J_X = 0$)	1.55	0.06	2.03	0.02	3.25	0.20	1.91	0.03	1.48	0.07	6.39	0.04	0.77	0.22	1.54	0.06	5.21	0.07
FADL vs. FADL-MIDAS ($J_X = 2$)	1.67	0.05	1.70	0.05	4.36	0.11	2.95	0.00	3.21	0.00	10.73	0.00	2.63	0.00	2.08	0.02	8.45	0.01

Table 5: Cross-sectional tests for predictive ability

Entries present the cross-sectional tests of the Mean, Median, and Upper Quartile of the Difference in MSFE and Diebold-Mariano tests. For each asset we construct the Difference in MSFE and the Diebold-Mariano statistics. We test whether the Mean, Median, and Upper Quartile of the cross-sectional distribution of these statistics is zero.

	Sample of 1999						**Sample of 1986**					
Forecast Horizon	1		2		4		1		2		4	
	stat	p-value	stat	p-value	stat	p-value	stat	p-value	stat	p-value	stat	p-value
Panel A: Difference in MSFE												
ADL vs ADL-MIDAS ($J_X = 0$)												
Mean	5.700	0.000	2.150	0.016	1.830	0.034	4.780	0.000	5.23	0.000	-0.130	0.449
Median	3.500	0.000	1.020	0.154	-0.193	0.423	2.700	0.003	3.97	0.000	-0.250	0.403
Upper Quartile	7.440	0.000	4.720	0.000	6.090	0.000	9.790	0.000	10.16	0.000	4.270	0.000
ADL vs ADL-MIDAS ($J_X = 2$)												
Mean	7.600	0.000	2.710	0.003	3.610	0.000	3.870	0.000	4.130	0.000	1.950	0.026
Median	4.220	0.000	1.150	0.125	1.950	0.026	1.470	0.071	3.610	0.001	0.840	0.199
Upper Quartile	14.23	0.000	6.740	0.000	7.830	0.000	6.770	0.000	8.350	0.000	6.240	0.000
FADL vs FADL-MIDAS ($J_X = 0$)												
Mean	9.840	0.000	5.320	0.000	0.520	0.301	0.820	0.204	2.450	0.007	-0.120	0.454
Median	7.410	0.000	3.010	0.001	0.404	0.343	0.230	0.408	1.930	0.027	0.630	0.264
Upper Quartile	2.980	0.003	5.450	0.000	6.140	0.000	4.090	0.000	2.220	0.027	2.280	0.022
FADL vs FADL-MIDAS ($J_X = 2$)												
Mean	8.820	0.000	2.530	0.006	-0.610	0.269	1.360	0.086	2.170	0.015	1.050	0.147
Median	7.040	0.000	2.210	0.014	-0.240	0.404	1.810	0.035	1.350	0.089	0.740	0.229
Upper Quartile	14.12	0.000	6.590	0.000	5.450	0.002	4.400	0.000	6.270	0.000	6.570	0.000
Panel B: Cross-sectional DM												
ADL vs ADL-MIDAS ($J_X = 0$)												
Mean	5.640	0.000	0.660	0.256	0.680	0.249	5.100	0.000	4.880	0.000	0.510	0.304
Median	3.190	0.000	1.190	0.237	0.250	0.800	4.100	0.000	3.940	0.000	0.860	0.392
Upper Quartile	3.38	0.001	4.94	0.000	4.73	0.000	7.770	0.000	8.81	0.000	4.92	0.000
ADL vs ADL-MIDAS ($J_X = 2$)												
Mean	7.220	0.000	0.960	0.168	2.560	0.005	2.420	0.008	3.56	0.000	0.550	0.290
Median	3.620	0.000	1.130	0.263	1.780	0.079	1.500	0.138	3.350	0.001	0.730	0.470
Upper Quartile	6.930	0.000	4.740	0.000	4.600	0.000	7.730	0.000	5.460	0.000	4.010	0.000
FADL vs FADL-MIDAS ($J_X = 0$)												
Mean	13.02	0.000	4.460	0.000	-0.330	0.369	-0.130	0.553	1.390	0.081	1.470	0.071
Median	8.070	0.000	3.470	0.001	-0.520	0.601	-0.240	0.809	1.670	0.099	1.350	0.180
Upper Quartile	6.65	0.000	4.730	0.000	2.800	0.006	4.470	0.000	6.400	0.000	7.12	0.000
FADL vs FADL-MIDAS ($J_X = 2$)												
Mean	10.41	0.000	2.690	0.004	0.150	0.440	-0.840	0.200	0.720	0.236	-0.370	0.355
Median	7.53	0.000	2.290	0.024	0.250	0.801	-1.600	0.114	1.390	0.168	-0.550	0.582
Upper Quartile	6.670	0.000	4.450	0.000	2.500	0.014	2.730	0.008	5.010	0.000	2.220	0.030

Table 6: Best Daily Financial Assets

Entries show the best daily assets for the FADL-MIDAS ($J_X = 2$) for samples of 1999 and 1986 and forecasting horizons, h=1,4. We highlight with light gray the top 10 percentile of the 65 assets, which are common in the samples of 1999 and 1986. Additionally, we highlight with darker gray the new predictors of 1999 that perform at least as well. In each case we present the corresponding rank (RK) and RMSFE of the predictor. For the sample of 1986 we also report the p-value of the forecast breakdown (FB) test.

Horizon 1											Horizon 4			
SAMPLE 1999			SAMPLE 1986				SAMPLE 1999			SAMPLE 1986				
RK	Assets	RMSFE	RK	Assets	RMSFE	FB test	RK	Assets	RMSFE	RK	Assets	RMSFE	FB test	
Commodities														
22	Wheat	0.58	41	Wheat	0.83	0.30	45	Wheat	0.93	7	Wheat	0.78	0.91	
6	WTI Oil Fut	0.50	64	WTI Oil Fut	0.87	0.25	61	WTI Oil Fut	0.99	22	WTI Oil Fut	0.90	0.57	
Corporate Risk														
85	1MEuro - FF	0.74	10	1MEuro - FF	0.73	0.54	1	1MEuro - FF	0.34	27	1MEuro - FF	0.92	0.98	
9	1MLIBOR	0.51					49	1MLIBOR	0.97	-	-	-	-	
1	1YLIBOR	0.36	11	1YLIBOR	0.74	0.35	62	1YLIBOR	1	47	1YLIBOR	0.98	0.99	
10	3MLIBOR	0.51	16	3MLIBOR	0.75	0.62	57	3MLIBOR	0.99	31	3MLIBOR	0.93	0.99	
4	6MLIBOR	0.47	17	6MLIBOR	0.75	0.40	38	6MLIBOR	0.88	32	6MLIBOR	0.93	0.99	
27	APFNF - AAF	0.59	-	-	-	-	4	APFNF - AAF	0.44	-	-	-	-	
51	APFNF - AANF	0.66	-	-	-	-	6	APFNF - AANF	0.49	-	-	-	-	
41	MBaa-10YTB	0.63	4	MBaa-10YTB	0.70	0.70	59	MBaa-10YTB	0.99	49	MBaa-10YTB	0.99	0.98	
42	MLA-10YTB	0.63	-	-	-	-	7	MLA-10YTB	0.50	-	-	-	-	
Equities														
7	DJI	0.50	5	DJI	0.70	0.57	26	DJI	0.77	8	DJI	0.80	0.93	
5	DJI Fut	0.49	-	-	-	-	24	DJI Fut	0.76	-	-	-	-	
11	MKT-RF	0.51	1	MKT-RF	0.65	0.82	21	MKT-RF	0.71	13	MKT-RF	0.84	0.88	
30	Nasdaq	0.60	13	Nasdaq	0.74	0.42	3	Nasdaq	0.42	4	Nasdaq	0.75	0.98	
38	Nasdaq 100	0.62	-	-	-	-	8	Nasdaq 100	0.52	-	-	-	-	
15	S&P 500	0.54	6	S&P 500	0.70	0.67	11	S&P 500	0.57	2	S&P 500	0.73	0.94	
13	S&P 500 Fut	0.52	3	S&P 500 Fut	0.69	0.66	9	S&P 500 Fut	0.56	1	S&P 500 Fut	0.72	0.92	
44	S&P500/VIX	0.64	9	S&P500/VXO	0.72	0.51	12	S&P500/VIX	0.58	3	S&P500/VXO	0.73	0.99	
91	SMB	0.79	26	SMB	0.81	0.33	2	SMB	0.40	37	SMB	0.95	0.99	
8	SPI	0.50	2	SPI	0.68	0.66	13	SPI	0.59	5	SPI	0.76	0.90	
86	UMD	0.75	18	UMD	0.76	0.45	5	UMD	0.46	6	UMD	0.77	0.96	
Foreign Exchange														
2	Canadian$/US$	0.45	58	Canadian$/US$	0.85	0.27	72	Canadian$/US$	1.04	58	Canadian$/US$	1.04	0.96	
Government Securities														
28	10YTB	0.59	7	10YTB	0.70	0.32	56	10YTB	0.99	26	10YTB	0.92	0.99	
24	6MTB - FF	0.58	35	6MTB - FF	0.82	0.34	10	6MTB - FF	0.57	43	6MTB - FF	0.97	0.94	
3	BEIR1F4	0.45	-	-	-	-	48	BEIR1F4	0.96	-	-	-	-	

Table 7: SPF forecasts for quarterly GDP growth

Entries present RMSFEs of quarterly SPF forecasts for real GDP growth relative to the RMSFE of RW for 1-, 2-, and 4-step ahead forecasts for 1986 sample. We compute the SPF forecasts of the GDP growth using the median and the mean forecast data for levels and denote the forecast for growth in the current quarter by horizon 1 as we do for forecasts based MIDAS with leads. Panel A includes the Clark-West (CW) for testing whether the difference in the MSFEs of SPF forecasts and the RW is zero and Panel B includes one-sided Diebold-Mariano (DM), Wilcoxon's signed rank, and Giacomini-White (GW)statistics for testing for equal forecasting accuracy between the 2DiscMSFE forecast combinations of MIDAS models with leads against the SPF forecasts.

Panel A: SPF forecasts against RW

Forecast Horizon	1		2		4	
	CW	p-val	CW	p-val	CW	p-val
Median SPF	2.33	0.01	1.65	0.05	1.00	0.16
SPF vs RW	2.21	0.01	1.59	0.06	1.07	0.14

Panel B: 2DiscMSFE MIDAS forecast combinations against SPF forecasts

Forecast Horizon	1						2						4					
	DM	p-val	W	p-val	GW	pval	DM	p-val	W	p-val	GW	pval	DM	p-val	W	p-val	GW	pval
Median SPF vs. ADL-MIDAS ($J_X = 2$)	−0.60	0.73	0.07	0.47	2.46	0.29	−0.41	0.66	−0.11	0.54	3.33	0.19	0.95	0.17	1.34	0.09	5.88	0.05
Median SPF vs. FADL-MIDAS ($J_X = 2$)	−0.02	0.51	0.61	0.27	3.90	0.14	0.93	0.18	1.85	0.03	1.82	0.40	3.06	0.00	3.17	0.00	11.46	0.00
Mean SPF vs. ADL-MIDAS ($J_X = 2$)	−0.45	0.67	0.11	0.45	2.80	0.59	−0.33	0.63	−0.09	0.54	3.37	0.19	0.97	0.22	0.97	0.16	6.80	0.03
Mean SPF vs. FADL-MIDAS ($J_X = 2$)	0.23	0.41	0.75	0.23	3.76	0.15	1.08	0.14	1.89	0.03	1.90	0.39	2.96	0.00	3.00	0.00	10.28	0.01

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, 2010a, Regression models with mixed sampling frequencies, *Journal of Econometrics* 158, 246–261.

——— , 2010b, Technical appendix: Should macroeconomic forecasters use daily financial data and how?, Available at `http://www.unc.edu/~eghysels/working_papers.html`.

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.

——— , 2008, Large dimensional factor analysis, in *Foundations and Trends in Econometrics,*vol. 3 . pp. 89–163 (now Publishers: Hanover).

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.

Chen, Xilong, and Eric Ghysels, 2010, 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.

Clark, T. E., and K. D. West, 2007, Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics* 138, 291–311.

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.

Faust, J., and J. H. Wright, 2009, Comparing greenbook and reduced form forecasts using a large realtime dataset, *Journal of Business and Economic Statistics* 27, 468–479.

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.

Giacomini, R., and B. Rossi, 2009, Detecting and predicting forecast breakdowns, *The Review of Economic Studies* 76, 669–705.

Giacomini, R., and H. White, 2006, Tests of conditional predictive ability, *Econometrica* 74, 1545–1578.

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 inflation 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, 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.

Harvey, D., S. Leybourne, and S. Newbold, 1998, Tests for forecast encompassing, *Journal of Business and Economic Statistics* 16, 254–259.

Hendry, D. F., and M. P. Clements, 2004, Pooling of forecasts, *Econometrics Journal* 7, 1–131.

Johannes, M.S., and N. Polson, 2006, Mcmc methods for continuous-time financial econometrics, in Y. Ait-Sahalia, and L.P. Hansen, ed.: *Handbook of Financial Econometrics* . pp. 87–115 (North Holland: Amsterdam).

Kitagawa, G., 1987, Non-gaussian state-space modelling of nonstationarity time series, *Journal of the American Statistical Association* 82, 1032–1041.

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.

Monteforte, Libero, and Gianluca Moretti, 2009, Real time forecasts of inflation: The role of financial variables, Bank of Italy.

Rapach, D. E., J. K. Strauss, and G. Zhou, 2009, Out-of-sample equity premium prediction: Combination forecasts and links to the real economy, *Review of Financial Studies* 23, 821–862.

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.

Smith, R.L., and J.E. Miller, 1986, A non-gaussian state space model and application to prediction of records, *Journal of the Royal Statistical Society, Series B (Methodological)* 48, 79–88.

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 G. Elliott, C. Granger, and A. Timmermann, 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.

Summers, L.H., 1986, Does the stock market rationally reflect fundamental values?, *Journal of Finance* 41, 591–601.

Tay, Anthony S., 2006, Financial variables as predictors of real output growth, Discussion Paper SMU.

——— , 2007, Mixing frequencies: Stock returns as a predictor of real output growth, Discussion Paper SMU.

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

Urich, T., and P. Wachel, 1984, The effects of inflation and money supply announcements on interest rates, *Journal of Finance* 39, 1177–1188.

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

Wasserfallen, W., 1989, Macroeconomics news and the stock market: Evidence from europe, *Journal of Banking and Finance* 13, 613–626.

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.

Appendix

A Forecasting Tests

For a sample size T, consider a sequence of $h-$step ahead out-of sample forecasts of Y_{t+h}, which is based on an in-sample window of size R and an out-of-sample (evaluation) window of size P such that $P = T - R - h + 1$. Let $f_t(\widehat{\beta}_t)$ be the time-t forecast based on recursive estimation of a model over the in-sample window at time t. Each time t forecast corresponds to a sequence of in-sample fitted values $\widehat{y}_j(\widehat{\beta}_t)$, with $j = h + 1, ..., t$.

A.1 Tests of predictive accuracy

Consider the out-of sample errors for model 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 and FADL-MIDAS using the time t forecast is given by

$$d_{i,t+h} = L(y_{t+h}, \widehat{y}^A_{i,t+h|t}) - L(y_{t+h}, \widehat{y}^B_{j,t+h|t}), \tag{A1}$$

where A=FADL and B=FADL-MIDAS. The DM test is basically a t-test that tests whether the expected loss differential is 0. Under the null this test is asymptotically normal and takes the following form,

$$DM_{i,h} = \frac{\overline{d}_{i,T}}{\sqrt{\widehat{V}(\overline{d}_{i,T})}} \tag{A2}$$

where $\overline{d}_{i,T} = \frac{1}{T} \sum_{t=R}^{T-h} d_{i,t+h}$. The asymptotic variance V can be estimated by the Newey-West (HAC) estimator since for multi-step forecasting ($h > 1$), the forecasts errors are assumed to follow a moving average process of at most $h - 1$ order.

The Wilcoxon's signed rank (W) test for squared losses can be viewed as an alternative to the DM test in the case of small samples and the presence of outliers. Both of these features make it an attractive alternative to the DM test for our sample of 1986 (for instance in the case of h=1 we have 31 observations in the evaluation period). The null hypothesis is that the loss differential $d_{i,t+h}$ has a median value zero. Under the null, W is also asymptotically Normal and it is defined by the following steps. Define the following indicator function which assigns the value 1 to all positive elements of $d_{i,t+h}$ and the value 0 otherwise.

$$l_+(d_{i,t+h}) = \begin{cases} 1, & d_{i,t+h} > 0 \\ 0, & o/w \end{cases} \tag{A3}$$

Then, the W test is given by the standardized sum of the positive ranks

$$W_{i,t+h} = \frac{\sum_{t=1}^{P-1} l_+(d_{i,t+h}) rank(|d_{i,t+h}|) - P(P+1)/4}{\sqrt{P(P+1)(2P+1)/24}}. \tag{A4}$$

In the case of ties, we rank all elements with the mean of the rank numbers that would have been assigned if they were different.

For our nested comparisons (e.g. RW against FADL-MIDAS) we employ the Clark and West (2007) (CW), which is an adjusted version of the Diebold and Mariano (1995) statistic, which also follows a standard normal distribution (e.g. FADL against FADL-MIDAS). The CW test can be defined as follows. Suppose model A is the small model (e.g. RW) and model B is a larger model that nests model A and define

$$d_{t+h}^{adj} = e_{A,i,t+h|t}^2 - [e_{A,i,t+h|t}^2 - (e_{A,i,t+h|t} - e_{B,i,t+h|t})^2]. \tag{A5}$$

Then the CW is simply the t-statistic for a zero coefficient that tests that the expected value of d_{t+h}^{adj} is zero.

One problem with the above tests is that they do not directly reflect the effect of estimation uncertainty on relative forecast performance. To deal with this problem we employ Giacomini and White (2006) (GW) test, which also permits a unified treatment of nested and nonnested models. The GW test differs from DM in two aspects: (i) the losses depend on estimates, rather than on their probability limits and (ii) the expectation is conditional on some information set $\mathbb{G}_t$. For instance, in the case of comparing the accuracy of FADL vs. FADL-MIDAS the null takes the form $H_0 : E((L(y_{t+h}, \widehat{y}_{i,t+h|t}^A) - L(y_{t+h}, \widehat{y}_{j,t+h|t}^B))|\mathbb{G}_t) = 0$. The GW test statistic is a Wald-type statistic of the following form

$$GW_{R,P}^{\eta} = n\overline{Z}'_{R,P}\widehat{\Omega}_P^{-1}\overline{Z}'_{R,P} \tag{A6}$$

where $\overline{Z}_{R,P} = P^{-1}\sum_{t=R}^{T-h} \eta_t \Delta L_{t+h}$, ΔL_{t+h} is the difference of loss functions at $t+h$, and η_t is a q

dimensional vector of test functions, which is chosen to embed elements of the information set that are expected to have potential explanatory power for the future difference in predictive ability. $\widehat{\Omega}_P$ is a consistent estimator of the asymptotic variance of $Z_{P,t+1}$. Note that in the case of multistep forecasts $\widehat{\Omega}_P$ is a Newey-West HAC estimator. Here, we follow Giacomini and White (2006) and use $\eta_t = (1, \Delta L_t)'$, which corresponds to the difference of squared residuals in the last period. Under the null of equal conditional predictive ability $GW^{\eta}_{R,P}$ asymptotically follows a χ^2_q distribution.

Next we describe our cross-sectional tests. Under the null of zero mean loss differential the statistic $DM_{i,h}$ for each asset is $N(0, V_{DM})$. We test whether the mean of the DM statistic for each asset is zero.

$$\overline{DM}_h = \sum_{i=1}^{N} DM_{i,h}/\sqrt{V_{DM}N} \tag{A7}$$

One problem with this test is that it depends on the estimation of the long run variance in $DM_{i,h}$. Given our small sample size we expect that the estimation of the variance will be inaccurate, especially in the case of $h = 4$. That is why we also report a cross-sectional test that is simply based on the difference in the MSFE for each asset i, $d_{i,h}$ rather than $DM_{i,h}$. Another problem with both of these cross-sectional tests is that they focus on the mean and that is why we also present results for the Median and top Quartile versions of these tests.

A.2 Encompassing Tests

Furthermore, we employ the Harvey, Leybourne, and Newbold (1998) (HLN) time-series test for forecast encompassing of the null that the forecast of models based on forecast combinations of a homogeneous class of assets encompasses forecast combinations across all daily predictors. That is forecast combinations based on all daily predictors adds no predictive power to forecasts based on combinations within a given class of assets. The HLN test amounts to testing the null of $\lambda = 0$ in the following auxiliary regression. We apply this test in the sample of 1986.

$$e^{Block}_{t+h} = \lambda(e^{Block}_{t+h} - e^{ALL}_{t+h}) + u_{t+h}. \tag{A8}$$

A.3 Tests for forecast breakdown

Finally, we employ the Giacomini and Rossi (2009) forecast breakdown (FB) test to examine whether the out-of sample performance of the forecast model is significantly worse than its in-sample performance in the sample of 1986.

Consider the out-of-sample loss corresponding to the forecast at time t $L_{t+h}(\widehat{\beta}_t) = L(Y_{t+h}, f_t(\widehat{\beta}_t))$ and the corresponding in-sample loss $L_j(\widehat{\beta}_t) = L(Y_j, \widehat{y}_j(\widehat{\beta}_t))$, where $j = h+1, ..., t$. Define a "surprise loss" at time $t+h$ as the difference between the out-of-sample loss at time $t+h$ and the average in-sample loss for $t = R, ..., T-h$:

$$SL_{t+h}(\widehat{\beta}_t) = L_{t+h}(\widehat{\beta}_t) - \overline{L}_t(\widehat{\beta}_t),$$

where $\overline{L}_t(\widehat{\beta}_t)$ is the average in-sample loss computed over the in-sample window implied by the forecasting scheme. Under the null hypothesis that the forecast is stable in the sense that out-of sample performance is not much worse than the in-sample, the mean of the "surprise loss" is zero. Then, we can define the asymptotically normal statistic

$$FB_{R,P,h} = P^{-1/2} \sum_{t=R}^{T-h} SL_{t+h}(\widehat{\beta}_t)/\widehat{V}_{R,P}, \tag{A9}$$

where $\widehat{V}_{R,P}$ is a HAC estimator given in Giacomini and Rossi (2009).

Table A1: Small Daily Dataset

Index	Short Name	Trans Code	Sample 1984	Definition
				Commodities
1	RJ CRB	5	1	Reuters/Jefferies CRB Futures Price Index: All Commodities (1967$\bar{1}$00)
2	Brent Oil	5	0	Europe Brent Spot Price FOB (Dollars Per Barrel)
3	Silver	5	1	S&P GSCI Silver Index (Dec-29-72=100)
4	PL-NYD	5	1	Platinum Cash Price (US$/Ounce)
5	Zinc	5	0	S&P GSCI Zinc Index (Dec-31=90=100)
6	XPD-D	5	0	Palladium (USD per Troy Ounce)
7	Wheat	5	1	S&P GSCI Wheat Index (Dec-31-69=100)
8	C-US2D	5	1	Corn Spot Price (US$/Bushel)
9	Soyb	5	1	S&P GSCI Soybeans Index (Dec-31-69=100)
10	Cotton	5	1	S&P GSCI Cotton Index
11	Sugar	5	1	S&P GSCI Sugar Index (Dec-29-72=100)
12	Coffee	5	0	S&P GSCI Coffee Index (Dec-31-80=100)
13	Cocoa	5	1	S&P GSCI Cocoa Index (Dec-30-83=100)
14	BO1599D	5	1	Soybean Oil Cash Price (Cents/Pound)
15	OATS-D	5	1	Oat Spot Price (US$/Bushel)
16	Cattle	5	1	S&P GSCI Live Cattle Index (Dec-31-69=100)
17	Hogs	5	1	S&P GSCI Lean Hogs Index (Dec-31-75=100)
18	Gold	5	1	S&P GSCI Gold Index
19	Aluminum	5	0	S&P GSCI Aluminum Index (Dec-31-90=100)
20	WTI Oil	5	1	Commodity Prices: Crude Oil, West Texas Intermediate ($/Barrel)
21	Lead	5	0	S&P GSCI Lead Index (Dec-30-94=100)
22	Nickel	5	0	S&P GSCI Nickel Index (Dec-31-92=100)
23	Tin	5	0	LME Tin: Closing Cash Price ($/Metric Tonne)
24	WC1-ID	5	1	CBOT Wheat Futures Prices
25	CC1-ID	5	1	CBOT Corn Futures Prices
26	SC1-ID	5	1	CBOT Soybean Futures Prices
27	CTC1-D	5	1	Cotton Futures Prices
28	Sugar-Fut	5	1	World Sugar Futures Price: 1st Expiring Contract Settlement (Cents/Lb)
29	KCC1-D	5	1	CSCE Coffee Futures Prices
30	CCC1-D	5	1	CSCE Cocoa Futures Prices (USD/Metric Ton)
31	BOC1-D	5	1	Soybean Oil Futures Price (Cents/Pound)
32	OC1-ID	5	1	Oat Futures Price
33	LCC1-D	5	1	Live Cattle Futures
34	LHC1-D	5	0	Live Hog Futures
35	GCC1-D	5	1	COMEX Gold Futures Prices
36	Alum Fut	5	0	LME Aluminum, 99.7% Purity: Closing 3-Month Forward Price ($Metric/Tonne)
37	WTI Oil Fut	5	1	Light Sweet Crude Oil Futures Price: 1St Expiring Contract Settlement ($/Bbl)
38	Lead Fwd	5	0	LME Lead: Closing 3-Month Forward Price ($/Metric Tonne)
39	Nickel Fwd	5	0	LME Nickel: Closing 3-Month Forward Price ($/Metric Tonne)
40	Tin Fwd	5	0	LME Tin: Closing 3-Month Forward Price ($/Metric Tonne)

Table continued on next page ...

Table A1 continued

Index	Short Name	Trans Code	Sample 1984	Definition
				Corporate Risk
1	LIBOR	2	0	Overnight London Interbank Offered Rate (%)
2	1MLIBOR	2	0	1-Month London Interbank Offered Rate (%)
3	3MLIBOR	2	1	3-Month London Interbank Offered Rate (%)
4	6MLIBOR	2	1	6-Month London Interbank Offered Rate (%)
5	1YLIBOR	2	1	One-Year London Interbank Offered Rate (%)
6	1MEuro-FF	1	1	1-Month Eurodollar Deposits (London Bid) (% P.A.) *minus* Fed Funds
7	3MEuro-FF	1	1	3-Month Eurodollar Deposits (London Bid) (% P.A.) *minus* Fed Funds
8	6MEuro-FF	1	1	6-Month Eurodollar Deposits (London Bid) (% P.A.) *minus* Fed Funds
9	APFNF-AANF	1	0	1-Month A2/P2/F2 Nonfinancial Commercial Paper (% Per Annum) *minus* 1-Month Aa Nonfinancial Commercial Paper (% Per Annum)
10	APFNF-AAF	1	0	1-Month A2/P2/F2 Nonfinancial Commercial Paper (% Per Annum) *minus* 1-Month Aa Financial Commercial Paper (% Per Annum)
11	TED	1	1	3Month Tbill *minus* 3-Month London Interbank Offered Rate (%)
12	MAaa-10YTB	1	1	Moody's Seasoned Aaa Corporate Bond Yield (% P.A.) *minus* Y10-Tbond
13	MBaa-10YTB	1	1	Moody's Seasoned Baa Corporate Bond Yield (% P.A.) *minus* Y10-Tbond
14	MLA-10YTB	1	0	Merrill Lynch Corporate Bonds: A Rated: Effective Yield (%) *minus* Y10-Tbond
15	MLAA-10YTB	1	0	Merrill Lynch Corporate Bonds: Aa Rated: Effective Yield (%) *minus* Y10-Tbond
16	MLAAA-10YTB	1	0	Merrill Lynch Corporate Bonds: Aaa Rated: Effective Yield (%) *minus* Y10-Tbond
				Equity
1	S&P500	5	1	S&P 500 Stock price index (1941-43=10)
2	S&P500 Fut	5	1	S&P 500 Futures price: 1st expiring contract settlement (Index)
3	SPI	5	1	S&P 500 Industrial stock price index (1941-43=100)
4	DJI	5	1	Stock price averages: Dow Jones 30 Industrials, NYSE (close)
5	DJI Fut	5	0	Dow Jones Industrials Futures Contract
6	Nasdaq	5	1	Stock price index:Nasdaq Composite (2/5/71=100)
7	Nasdaq100	5	0	Stock price index:Nasdaq 100
8	VIX or VXO	1	1	CBOE market volatility index, VIX (1999 Sample) or VXO (1986 Sample)
9	MKT-RF	1	1	MKT *minus* RF
10	SMB	5	1	French Data
11	UMD	5	1	French Data
12	HML	5	1	French Data
13	S&P500toVIX	5	1	S&P500/VIX

Table continued on next page ...

Table A1 continued

Index	Short Name	Trans Code	Sample 1984	Definition
				Foreign Exchange Rate
1	EFXbroad	5	0	Effective Exchange Rate-Broad
2	EFXmajor	5	1	Effective Exchange Rate-Major
3	Canadian$/US$	5	1	Canada: Spot Exchange Middle Rate, NY close (Canadian$/US$)
4	Euro/US$	5	0	Europe: Spot Exchange Middle Rate, NY close (Euro/US$)
5	Japanese Yen/US$	5	1	Japan: Spot Exchange Middle Rate, NY close (Yen/US$)
6	Swiss Franc/US$	5	1	Switzerland: Spot Exchange Middle Rate, NY close (Francs/US$)
7	UK/US$	5	1	United Kingdom: Spot Exchange Middle Rate, NY close (Pounds/US$)
				Government Securities
1	FF	2	1	Federal Funds [Effective] Rate (% P.A.)
2	3MTB	2	1	3-month Treasury Bills, Secondary Market (% P.A.)
3	6MTB	2	1	6-month Treasury Bills, Secondary Market (% P.A.)
4	1YTB	2	1	1-year Treasury Bill Yield at Constant Maturity (% P.A.)
5	10YTB	2	1	10-year Treasury Bond Yield at Constant Maturity (% P.A.)
6	BEIR5	1	0	US Inflation Compensation: Continuously Compounded 5-year Zero-Coupon Yield (%)
7	BEIR10	1	0	US Inflation Compensation: Continuously Compounded 10-year Zero-Coupon Yield (%)
8	BEIR1F4	1	0	US Inflation Compensation: Coupon-Equivalent One-year Forward Rate From Four to Five Years
9	BEIR1F9	1	0	US Inflation Compensation: Coupon-Equivalent One-year Forward Rate From Nine to Ten Years
10	BEIR5-10	1	0	US Inflation compensation: Coupon-Equivalent Five to Ten Year Forward Rate
11	6MTB-FF	1	1	6-month Treasury Bill Market Bid Yield at Constant Maturity (%) *minus* Fed Funds
12	1YTB-FF	1	1	1-year Treasury Bill Yield at Constant Maturity (% P.A.) *minus* Fed Funds
13	10YTB-FF	1	1	10-year Treasury Bond Yield at Constant Maturity (% P.A.) *minus* Fed Funds
14	6MTB-3MTB	1	1	6-month Treasury Bill Yield at Constant Maturity (% P.A.) *minus* M3-Tbills
15	1YTB-3MTB	1	1	1-year Treasury Bill Yield at Constant Maturity (% P.A.) *minus* M3-Tbills
16	10YTB-3MTB	1	1	10-year Treasury Bond Yield at Constant Maturity (% P.A.) *minus* M3-Tbills
				Coincident Indicator
1	ADS	1	1	Daily Aruoba-Diebold-Scotti Business Conditions Index