Should macroeconomic forecasters use daily financial data and how?*

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First Draft: May 2009
This Draft: October 4, 2010

Abstract

We introduce easy to implement regression-based methods for predicting quarterly real economic activity that rely on forecast combinations of MIDAS regressions. Our analysis is designed to elucidate the value of daily information using MIDAS regressions in improving traditional forecasts based on aggregated data and how these regressions can be used to provide real-time forecast updates of the current quarter (nowcasting). Our empirical study covers 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 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 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.

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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. 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 weekly or potentially intra-daily) financial data with quarterly (or monthly) macroeconomic series when one wants to predict over relatively long horizons, like one year ahead, and (2) how to summarize or extract the relevant information from the vast cross-section of daily financial series. In this paper we address both challenges.

Not using the readily available high frequency 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 quarterly macro forecasts and (2) one looses information through temporal aggregation. Using daily financial data has several advantages for quarterly macro forecasts. First, financial data are observed without measurement error and are not subject to revisions as opposed to most macroeconomic indicators. Second, certain financial markets often react to news about the state of the economy faster than other markets. Third, certain markets are forward looking such as futures and options markets. Regarding the loss of information through aggregation, there are a few studies that addressed the mismatch of sampling frequencies in the context of macroeconomic forecasting. These studies use state space models, which consist of a system with two types of equations, measurement equations linking observed series to a latent state process, and state equations describing the state process dynamics. The Kalman filter can then be used to predict low frequency macro series, using both past high and low frequency observations. This system of equations requires a lot of parameters, for the measurement equation, the state dynamics and their error processes.[2] Such state space models are far more complex in terms of specification,

[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

estimation and computation of forecasts, compared to the approach proposed in this paper. If we were to use large sets of daily series, this means formulating a large system of equations that describes the dynamics of all the series involved. This approach is often feasible when dealing with a small system (e.g. Aruoba, Diebold, and Scotti (2009) involving 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. 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 with financial aggregates - as is typically done - is also problematic in terms of estimation. Andreou, Ghysels, and Kourtellos (2010a) show that the estimated slope coefficient of a regression model that impose 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 in large cross-sections of high frequency financial data, nor the potential usefulness of such

(2009), Ghysels and Wright (2009), Kuzin, Marcellino, and Schumacher (2009), among others.

[3]MIDAS regressions were suggested in recent work by Ghysels, Eric and Santa-Clara, Pedro and Valkanov, Ross (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 (2009), Engle, Ghysels, and Sohn (2008), Forsberg and Ghysels (2006), Ghysels, Santa-Clara, and Valkanov (2005), León, Nave, and Rubio (2007), among others.

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

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

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 used again the state space setup - and therefore face the same computational complexities pointed out earlier. Here too, MIDAS regressions provide a relatively easy to implement alternative. The simplicity of the approach allows us to produce nowcasts with potentially a large set of real-time data feeds. More importantly, we show that MIDAS models with leads can be extended beyond nowcasting the current quarter to forecast multiple quarters ahead.

To deal with the potential large cross-section of daily series we propose two approaches: (1) forecast combinations with a large set of daily financial series, and (2) extract a small set of daily financial factors from a large cross-section of around one thousand financial time series, which cover five main classes of assets - Commodities, Corporate Risk, Equities, Foreign Exchange, and Government Securities (fixed income). These factors are then used in our forecasting models as in (1) above.

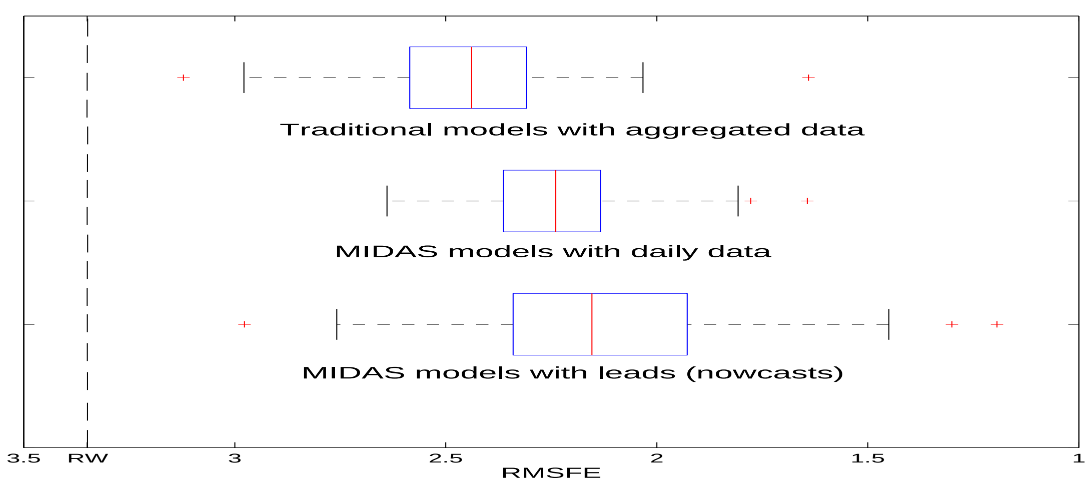


Figure 1: Boxplots

We provide a succinct preview of the forecasting gains due to the use of daily financial data

[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.

in Figure 1. It contains boxplots displaying the forecast performance for one quarter ahead GDP growth using three methods: (1) traditional models using aggregated financial series, (2) MIDAS forecasts and (3) MIDAS with leads corresponding to nowcasting.[7] Our results pertain to forecasting GDP growth during the turbulent times of the financial crisis, namely forecasting US economic activity for the period 2006-2008.

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 Government Securities (fixed income), Equities, Corporate Risk, Commodities, and Foreign Exchange series used by forecasters. 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 the daily observations. Finally, the third boxplot contains a nowcast of GDP growth two months into the quarter, so one has two months of real-time 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 see a substantial shift to the right as we move from the first to the second boxplot. This measures the cross-sectional distributional shift when we use MIDAS regressions and replace quarterly aggregates of financial assets with their daily observations. The third and final boxplot shows the shift when we continue to use MIDAS regressions but exploits 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 important gains in forecasting when daily data are used and also showing the additional flexibility of updating forecasts with the steady flow of daily data. 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 our quarterly and daily data. In sections 4.1 and 4.2 we present our

[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.

factor analysis and forecast combination methods, respectively. In section 5 we present our empirical results, respectively. Section 6 concludes.

2 MIDAS regression models

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

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

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 $p^Q_Y + q^Q_X + 1$ parameters to be estimated. Assume now that we would like to use instead the daily observations of the financial predictor series X. 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 $X^D_{N_D-j,t}$. A naive approach would be to estimate - in the case of p^Q_Y = $q^Q_X = 1$ the regression:

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

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 slope coefficients. A MIDAS regression approach consists of hyper-parameterizing the polynomial lag structure in the above equation, yielding what we will call a $ADL - MIDAS(p^Q_Y, q^D_X)$ 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, to simplify notation, we will always take lags in blocks of quarterly sets of daily data, hence the notation. Following Ghysels, Santa-Clara, and Valkanov (2006) and Ghysels, Sinko, and Valkanov (2006), we use a two parameter exponential Almon lag polynomial

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

with $\theta = (\theta_1, \theta_2)$. This approach allows us to obtain a linear projection of high frequency data X_t^D onto Y_t^Q with a small set of parameters. Note that this yields a general and flexible function of data-driven weights.[8]

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

The comparison with temporal aggregation prompts us to consider two MIDAS regression models that allow for quarterly lags. First, define the following filtered parameter-driven

[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).

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 would be more suitable. We do not deal directly with these types of questions here, as they have been addressed notably in Bai, Ghysels, and Wright (2009) and Kuzin, Marcellino, and Schumacher (2009). However, some short answers to these questions are as follows.

First, it turns out that a MIDAS regression can be viewed as a reduced form representation of the linear projection that emerges from a state space model approach - by reduced form we mean that the MIDAS regression does not require the specification of a full state space

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

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 (2.3). 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 goes, 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 mis-specification. MIDAS regressions, in comparison, are frugal in terms of parameters and achieve the same goal. More parameters and a system of equations also means that estimation is more numerically involved - something that is not so appealing when dealing with large data sets - as we will.

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 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). The Kalman filter is typically used for nowcasting.

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 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

[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.

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.

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

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

There are various ways of how to hyper-parameterize the lead and lag MIDAS polynomials. Along with a complete list of MIDAS regression models this is discussed in the Appendix A3 of Andreou, Ghysels, and Kourtellos (2010b).

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 GDP forecasts. MIDAS with leads can be viewed as updates - timed as frequently - of not only current quarter GDP forecasts, but any future horizon 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 lead 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).

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 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 US quarterly growth rate of real Gross Domestic Product (GDP) - only available at a quarterly frequency. We are interested in quarterly forecasts of GDP growth as it is one of the key macroeconomic measures in the literature. Moreover, policy makers report quarterly forecasts such as, for instance, the Fed's Greenbook forecasts. Similarly, it is one variables covered in most surveys of macroeconomic forecasts such as, for instance, the Survey of Professional Forecasters, Blue Chip Economic Indicators, among others. Finally, one of the popular approaches in forecasting GDP growth is based on factor models (e.g. Forni, Hallin, Lippi, and Reichlin (2005), Stock and Watson (2007), and Stock and Watson (2008a)), using quarterly data which is mainly due to the availability of most macroeconomic variables at that frequency.

We study a recent sample period of 1/1/1999-31/12/2008 (40 quarters) for at least three reasons: First, this period provides a new set of daily financial predictors relative to most of the existing literature on forecasting, including new series such as Corporate risk spreads (e.g. the A2P2F2 minus AA nonfinancial commercial paper 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 (e.g. see, for instance, the comprehensive review in Stock and Watson (2003)) but have also been recently 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 Fed's Federal Open Market Committee (FOMC) meetings and the VIX often coined as the stock market fear-index.

Second, for this period the daily data availability allows us to study the role of a large cross-section of daily financial predictors by extracting a small number of daily factors to examine whether these improve macroeconomic forecasts in the last two decades over other methods used in the existing literature.

Third, we note that this recent period belongs to the post 1985 Great moderation era, which is marked as a structural break in many US macroeconomic variables (Stock and Watson (2003), Bai and Ng (2005), Van Dijk and Sensier (2004)) and has been documented that it is more difficult to predict such key macroeconomic variables (D'Agostino, Surico, and Giannone (2009), Rossi and Sekhposyan (2010)) vis-à-vis simple univariate models such as the Random Walk (RW) and Atkeson-Ohanian (AO) models (Atkeson and Ohanian (2001), Stock and Watson (2008b)) (for economic growth and inflation, respectively) and vis-à-vis the pre-1985 period. 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.

One problem with the sample of 1999 is that the time series is too short and hence standard inference may not be possible. To overcome this criticism we also study the longer period of 1986:Q1-2008:Q4 (92 quarters), which involves a smaller cross-section of just 65 series due to data availability.

In particular, we use three databases observed at two different sampling frequencies: one quarterly database of macroeconomic indicators and two daily databases of financial indicators. We will generally 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 individual 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 by first differencing so as to ensure stationarity. Details of the transformations can be found in a companion document Technical Appendix (see Andreou, Ghysels, and Kourtellos (2010b)) - henceforth we will refer to this as the online Appendix.

The first is a quarterly dataset of 69 macroeconomic 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, which we will call macro 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 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 the online Appendix of the paper (see Andreou, Ghysels, and Kourtellos (2010b)).

We also create a third smaller daily database, 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 (4584 trading days) from the above five categories of financial assets. 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

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

former involves less missing missing observations when balancing the short cross-section. These daily predictors are proposed in the literature as good predictors of economic growth. The online Appendix presents again the details of these predictors (variables names, short description, transformations and data source). Describing briefly these daily predictors we categorize them into five classes and use: (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&P500 Implied 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), Laurent (1989), Harvey (1989b), Harvey (1988), Stock and Watson (1989), Estrella and Hardouvelis (1991), Fama (1990), Mishkin (1990b), Mishkin (1990a), Hamilton and Kim (2002), Ang, Piazzesi, and Wei (2006)) and inflation compensation series (of different maturities and forward contracts) (e.g. Gurkaynak, Sack, and Wright (2010)). Last but not least, we consider the daily Aruoba, Diebold and Scotti (ADS) Business Conditions Index, 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 complements our daily factors extracted from our large cross-section of merely 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. At the outset we should note that the problem we consider is of general interest beyond the application of the current paper. Namely, very often we face the problem of forecasting a low frequency series (quarterly in this case, but it could be any frequency - less often observed than the high frequency series) using a potentially large cross section of high frequency information (and past low frequency data).

The first strategy involves extracting factors from two large cross-sections observed at different frequency described in section 3. 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 GDP growth, are used in MIDAS regressions as predictors of GDP growth. Perhaps we should add a footnote here explaining why we do not consider a mixed frequency factor model?

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 (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), Bai (2003), Forni, Hallin, Lippi, and Reichlin (2000), Forni, Hallin, Lippi, and Reichlin (2005), Stock and Watson (1989), Stock and Watson (2003), among many others. 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 (2006) and Stock and Watson (2002b) 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 from 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 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.[12]

In particular, using the quarterly common factors we extend the MIDAS regression models. For instance, equation (2.3) generalizes to the $FADL-MIDAS(p_Y^Q, p_F^Q, q_X^D)$ model

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

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 equation (4.2) 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 real markets and therefore the latest news are incorporated into asset prices while the macroeconomic factors and lagged GDP growth remain unrevised.

The next question is how we construct the factors. We estimate both the quarterly macroeconomic factors and the daily financial factors using a Dynamic Factor Model (DFM)

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

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.[13]

We choose this particular factor model for two main reasons. First, this DFM 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.[14] DFM using principal components, which yields consistent estimates of the common factors if $N \to \infty$ and $T \to \infty$. The condition $\sqrt{T}/N \to \infty$ ensures that the estimated coefficients of the forecasting equations (e.g. FADL-

[13]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 (Bai and Ng (2008)).

[14]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.

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.[15]

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 highly with Industrial Production and Purchasing Manager's index whereas the second quarterly factor correlates highly with Employment and NAPM inventories index. These results are consistent with Stock and Watson (2008a) that use a longer time-series sample as well as Ludvigson and Ng (2007) and Ludvigson and Ng (2009) that use a different panel of US data. Interestingly, although our quarterly database excludes 20 financial variables from the Stock and Watson database, namely the variables which are available at daily frequency, our first two factors correlate almost perfectly with those of Stock and Watson (with correlation coefficients equal to 0.99 and 0.98 for factors 1 and 2, respectively). Hence, the excluded aggregated daily series do not seem to play an important role for extracting the first two factors for the period 1999:Q1-2008:Q4.

In the case of the daily financial factors we find that all three ICP criteria always suggest the maximum number of factors. So in order 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: $F_{CLASS} = (F^D_{COMM}, F^D_{CORP}, F^D_{EQUIT}, F^D_{FX}$, and $F^D_{GOV}))$. As we will explain in the following section we employ forecast combinations of these daily factors rather than forecasting 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

[15] 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.

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 A2 of the companion document Andreou, Ghysels, and Kourtellos (2010b)). The eigenvalues appear rather stable with the exception of some small instability towards the end of the sample, especially for the eigenvalues of F^D_{CORP}. The first principal component appears to capture at least 40% in all cases and as much as 75%, 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 and the first daily factor from each of the five classes of assets, respectively. In general, all five daily factors are characterized by volatility clustering and with recent high volatility period. Notable exceptions are $F^D_{ALL,5}$ and $F^D_{CORP,1}$, which both exhibit 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 attach an economic interpretation to five daily financial factors extracted from all assets. 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 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 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 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 and associated forecasts, combination forecasts are (time-varying) weighted averages of the individual forecasts,

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

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

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 Stock and Watson (2004) and Stock and Watson (2008b). This method accounts for the historical performance of each individual by computing the combination forecast as a weighted average of the individual forecasts, where the weights are inversely proportional to the square of the discounted MSFE (henceforth denoted 2DiscMSFE) with a discount factor of 0.9 to attach 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 $\kappa = 1, 2$. 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. [16]

For robustness purposes we also report in in a companion document Technical 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). [17]

Operationally, we proceed as follows. We compute forecasts based on six families of models with single predictors based on (1) daily/aggregated financial assets and (2) daily/aggregated 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

[16] 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.

[17] 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.

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 lagged structures based on a fixed lagged scheme or an AIC based criterion. Second, we select the best model in terms of its out-of sample performance. And third, given a family of models we provide forecast combinations of models with alternative assets or financial factors.[18]

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.[19] 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.

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, $T_0 = 2001 : Q1$. $T_1 = 2006 : Q1 + h$, and $T_2 = 2008 : Q4 - h$ or 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

[18] 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.

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

distributions of ADL, FADL, ADL-MIDAS as well as the FADL and FADL-MIDAS models appears in Figure A1 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 5.1. The following two 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. Finally, we present our forecasting tests in section A.

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 GDP growth we address the following questions.

(i) *Do reduced-form MIDAS regressions improve benchmark forecasts of quarterly economic activity?*

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 AR and FAR models. These findings hold for all forecast horizons, both samples, and for both daily financial assets and daily financial factors.[20] We should note that quarterly (real) macroeconomic factors appear to play

[20]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

a major role in forecasting quarterly 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 period, namely 1959-1998, also find that models using a small number of factors can provide dramatic forecasting gains over benchmark forecasts.

(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 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?*

regression models using daily assets but also carries over to traditional models based on aggregated assets.

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 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 as well as the value of the RMSFE for the RW. In particular, Panel A of Table 2 reports the benchmarks of RW, AR models and quarterly FAR models. Panel B reports the traditional ADL models and quarterly factor ADL (FADL) models based on aggregated financial assets or financial factors as well as the corresponding MIDAS regression models based on daily financial assets or factors, namely, the ADL-MIDAS and FADL-MIDAS regression models without leads ($J_X = 0$) and with leads ($J_X = 2$). The results are grouped into the 1999 and 1986 samples based on the data availability of the daily financial assets. The forecast combination results report RMSFEs for 93 and 65 assets in 1999 and 1986, respectively. The forecast combination results for financial factors are based on the sample of 1999 and consider combinations of the first 5 financial factors based on all 988 daily series, F^D_{ALL}, as well as the 25 block factors, F^D_{CLASS}, which include the first 5 factors of 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 leading information in FADL-MIDAS regression models that yields the highest gains. For both short and long forecasting horizons, $h = 1$ and 4, the FADL-MIDAS regression models with leads using combinations of the homogeneous sets of 25 daily financial factors 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 for 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 benchmark 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 to those obtained for the longer sample of 1986 and the subset of 65 assets, we still find that FADL-MIDAS regression models with leads yield the highest gains, which are however relatively smaller compared to 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 ARs 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 1999 for $h = 1$ and 2 the gains of FADL-MIDAS models vis-à-vis the RW, AR and FAR models are similar across the three subsets of assets whereas for $h = 4$ it is the set of 93 assets and 25 daily factors 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 GDP growth forecasts.

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

We now turn to compare the RMSFEs of FADL-MIDAS regression models with and without leads ($J_X = 0$) and ($J_X = 2$), respectively. For $h = 1$ the FADL-MIDAS models with leads provides higher gains than the corresponding model without leads. This finding is consistent for both daily assets and daily financial factors. For instance, for the 1999-2008 sample period for $h = 1$ the combinations of FADL-MIDAS with leads based on the 93 daily predictors, the 25 daily homogeneous factors and the 5 daily financial factors provide 18%, 11% and 30% gains, respectively, over the corresponding FADL-MIDAS without leads. However, in the 1999 sample for $h = 4$ the FADL-MIDAS regression models with leads deliver gains of upto 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 predictors 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 5 daily factors and FADL as well as FADL-MIDAS models without leads.

Figures 5 - 6 provide recursive time plots of RMSFEs relative to the RW and combinations weights over the evaluation period of 2006-2008. 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 $h = 4$.[21]

[21]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.

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 our results suggest that the gains of MIDAS regression models, especially those of the FADL-MIDAS with leads are not symptomatic but they are rather robust at most points of time in our evaluation period.

Finally, we 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.

5.3 Forecast evaluations

As mentioned in section 3 the short time-series nature of the sample of 1999 makes standard time-series statistical inference rather infeasible and hence we can only provide formal time-series testing for the sample of 1986. Given this challenge we propose a cross-sectional testing for the sample of 1999 in the spirit of Granger and Huang (1997). Appendix A provides a detailed description of the tests.

For the sample of 1986, we use one-sided Diebold and Mariano (1995) tests and West (1996)

(DMW), Wilcoxon signed rank (W) tests, 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.[22]. To deal with both problems we also employ Giacomini and White (2006) (GW), 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) and West (1996) statistic. For the sample of 1999, we employ two cross-sectional statistics of equal predicting 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. The distribution of the statistics is bootstrapped with replacement from the asset based empirical distribution. Similarly, the second cross-sectional test is based on the standardized difference in MSFE, which is the DMW for each asset. The advantage of the latter is that it takes into account the uncertainty from the time-series dimension, albeit concerns about the accuracy of the estimation of the long run variance given the small sample.

Table 4, presents the equal forecasting accuracy test of CW in Panel A along with the DMW, W, GW in Panel B for the sample of 1986.[23] 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 DMW and W that test for equal forecasting accuracy between forecast combinations of MIDAS regression models vis-à-vis those obtained from traditional model. In general we find that

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

[23]For DMW, 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.

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 turn to look deeper into our cross-section in order to identify if certain classes of financial assets drive the forecasting gains of US 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. In addition, for $h = 1$ the Government securities assets and corresponding factors perform equally well. Interestingly, combinations of Corporate risk assets using FADL-MIDAS with leads perform better than the corresponding factors in forecasting GDP growth for all h. Similar, albeit weaker, results are obtained for the 1986 sample.

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 ($J_X = 2$).[24] For the sample of 1999 and $h = 1$ we find that the Government Securities and Corporate Risk assets systematically provide the highest predictive accuracy. Equities are close but overall can be viewed as the third most important class in this case. Interestingly, Corporate Risk assets appear to be the least affected by the Lehman Brothers' fallout in the last quarter of 2008 and hence this class was singled out as the best performing class of predictors in the

[24]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.

Table 3. For $h = 4$ we find that Equities is by far the best performing class of assets. In fact Equities exhibited the highest gains during the 2004-2006 period but then suffered a sudden loss of predictive ability which is also apparent in the combination weights. Nevertheless, Equities appear to provide strong gains even during the end of the sample. Figure 9 repeats the analysis for the daily 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 appear to provide the most robust results, especially at the end of the sample. Interestingly, while combinations of daily factors from the class of Equities perform the best during 2007, they deteriorate substantially in 2008.

For the 1986 sample, 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. Table 6 presents the results which shows that the forecast combinations class of Equities and Corporate Risk alone can provide gains that encompass forecasts combinations across all 5 classes of assets.

Within the Corporate risk, Equity, and Government securities we identify the set of best predictors for $h = 1$ and 4 in the top 10 percentile of the RMSFEs distributions of the cross-section of assets in order to evaluate their stability with respect to the two samples of 1986 and 1999; see Table 7. It is interesting to note at the outset that in the Equities class the 9 assets that appear in the top quartile are similar in the two samples. For example in 1986, the S&P500 returns, excess 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.

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. This 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 7 we find that we always accept the null of no forecast breakdown. [25] This implies that our MIDAS forecasts are valid at least for the longer sample of 1986.

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.

6 Conclusion

We studied how to incorporate the information in daily financial into forecasting of quarterly 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

[25] This result even holds for the larger set of the best performing daily factors in the top quartile reported in Table A5 appearing in Andreou, Ghysels, and Kourtellos (2010b). The only notable exception is ADS in the case of $h = 1$.

one with leads does not suffer as much losses as the traditional models.

Finally, forecasting of 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

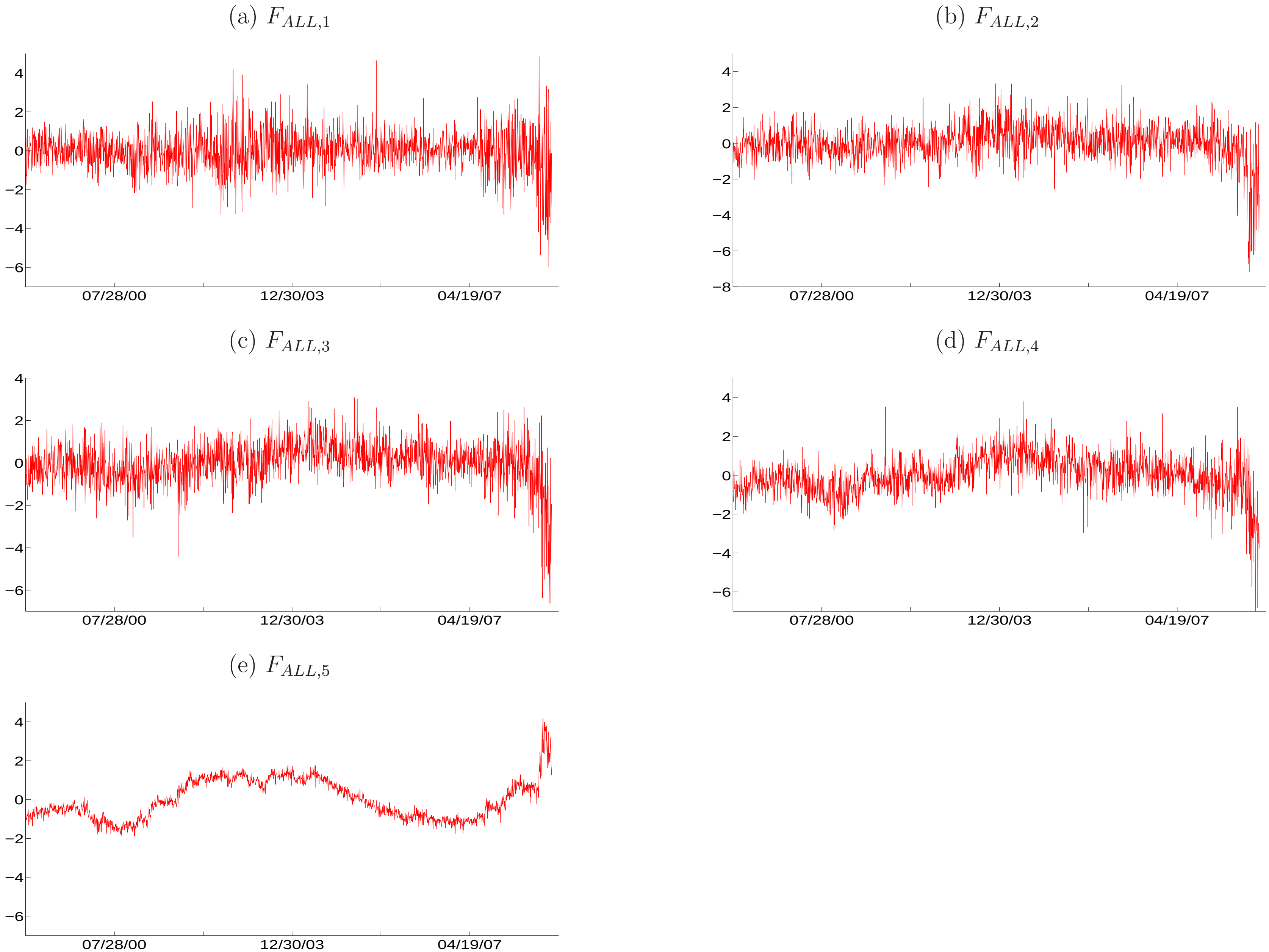


Figure 3: The first daily factors extracted from the 5 classes of assets

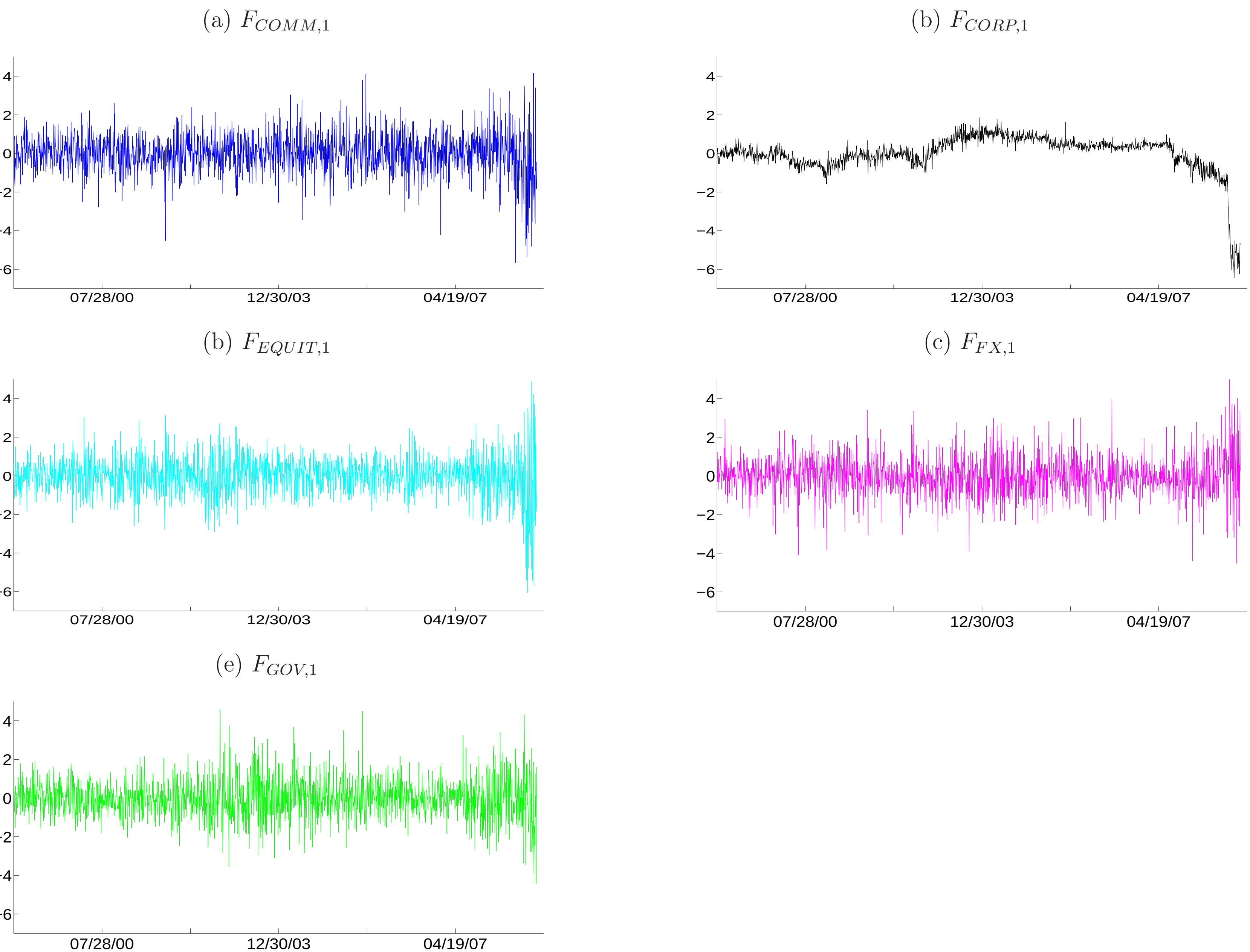
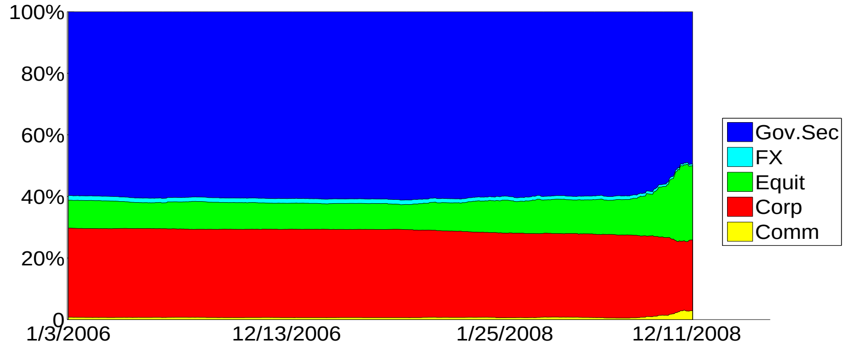
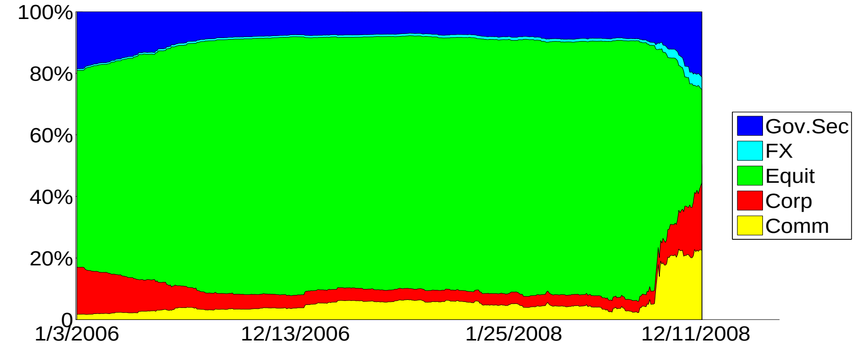


Figure 4: Sum of squared loadings for the daily financial factors extracted from *all* daily assets

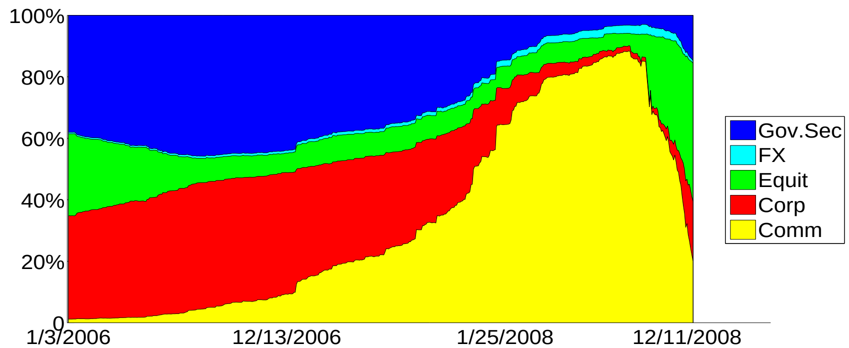
(a) $F_{ALL,1}$



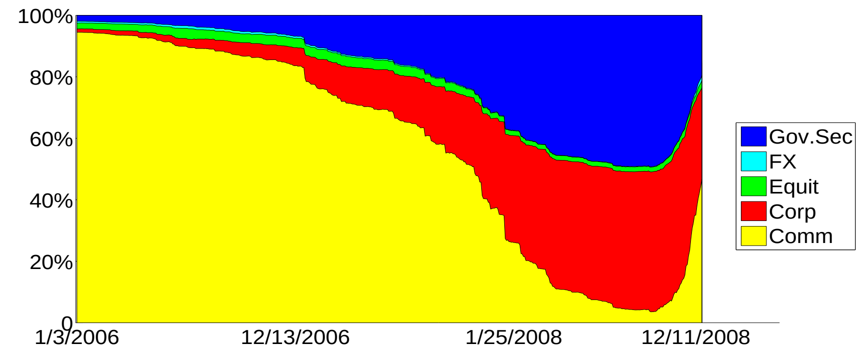
(b) $F_{ALL,2}$



(c) $F_{ALL,3}$



(d) $F_{ALL,4}$



(e) $F_{ALL,5}$

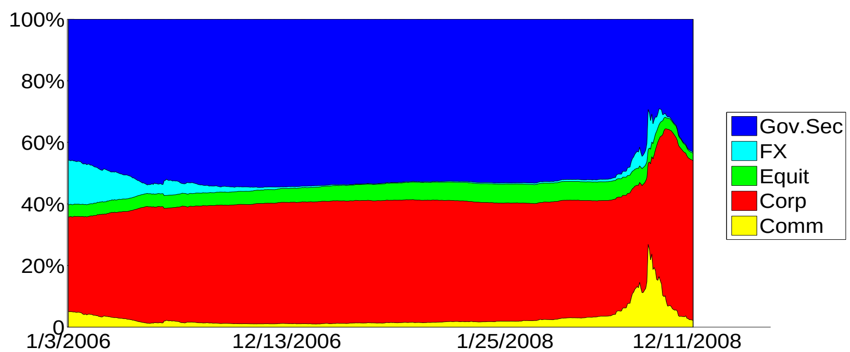
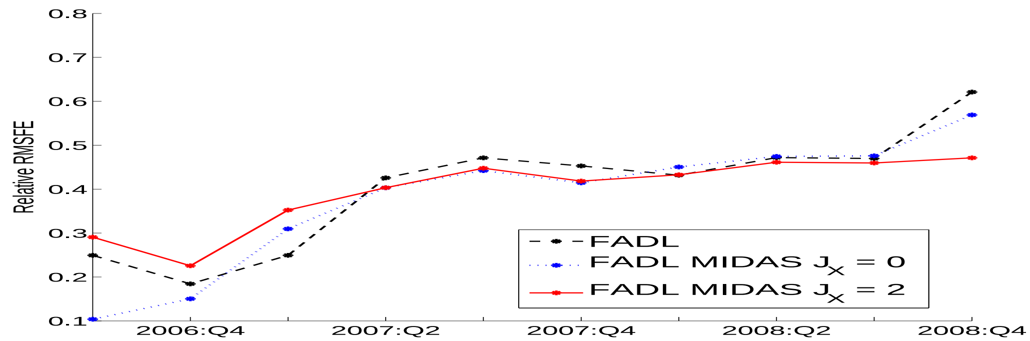
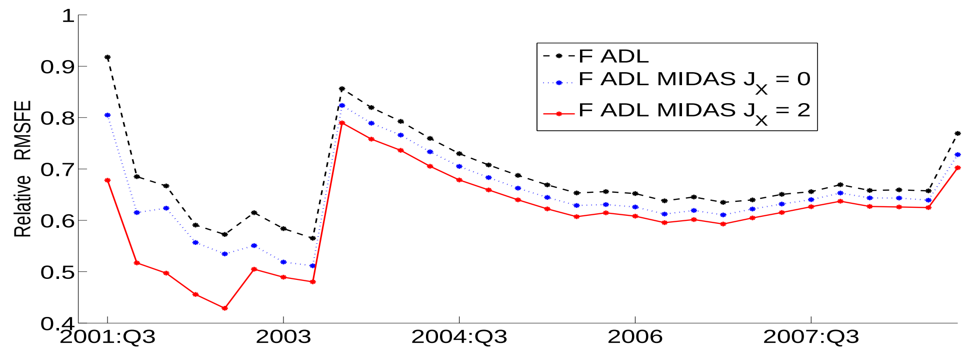


Figure 5: RMSFE of 2DiscMSFE forecast combinations for daily financial assets

(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

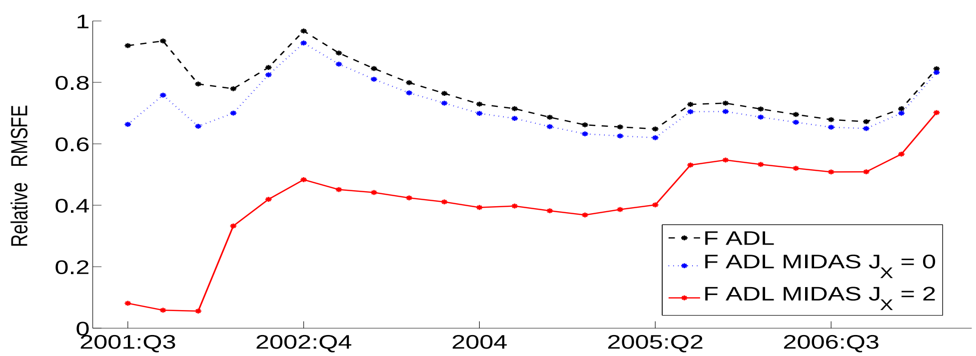
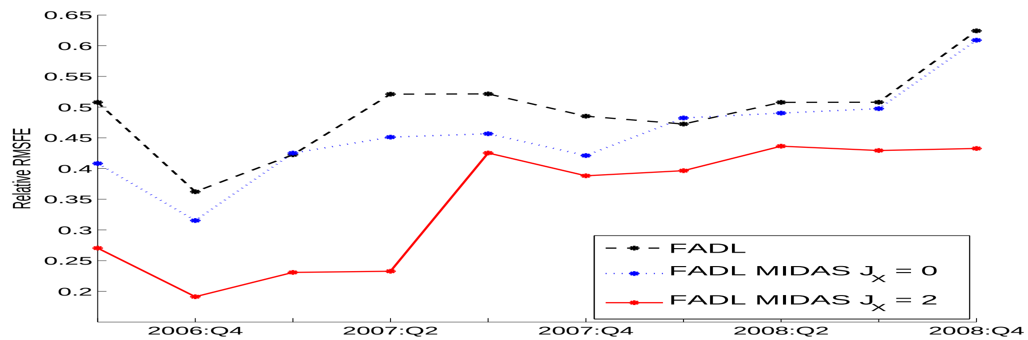
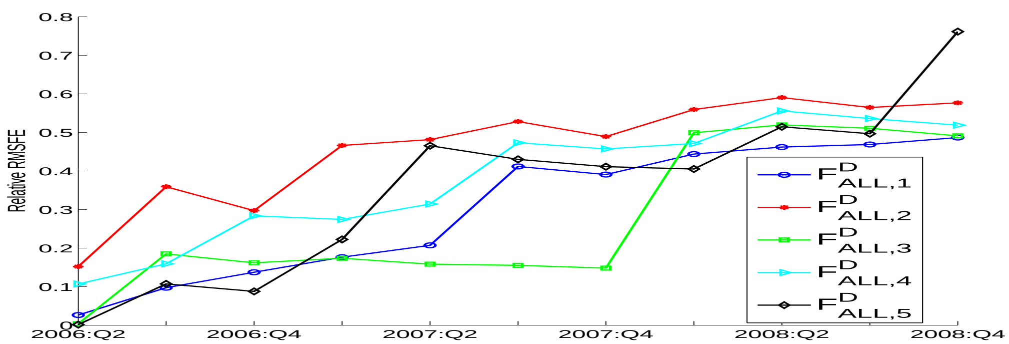


Figure 6: 5 daily financial factors extracted from *all* daily financial assets, ($F_{ALL,j}$, j=1,2,..,5)

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



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



(c) 2DiscMSFE combination weights, h = 1

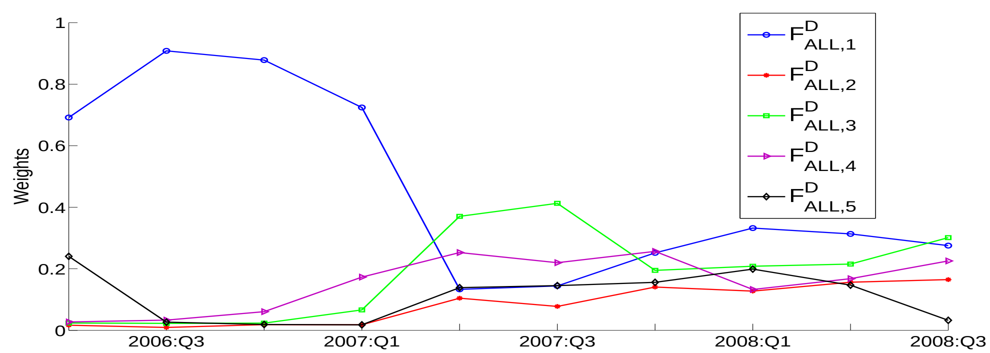
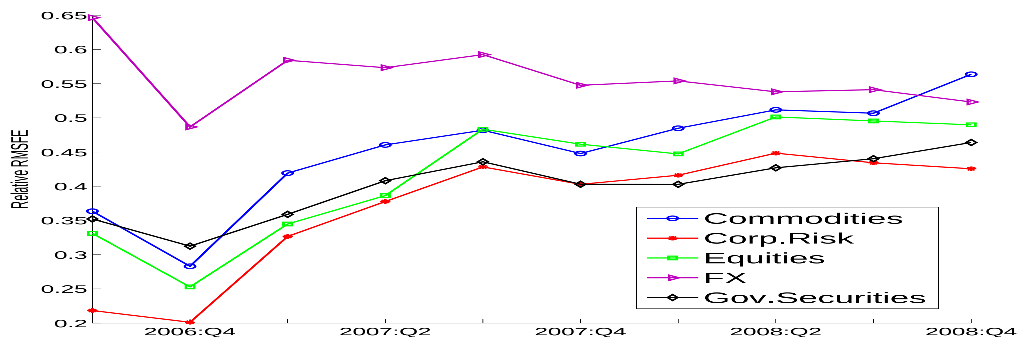
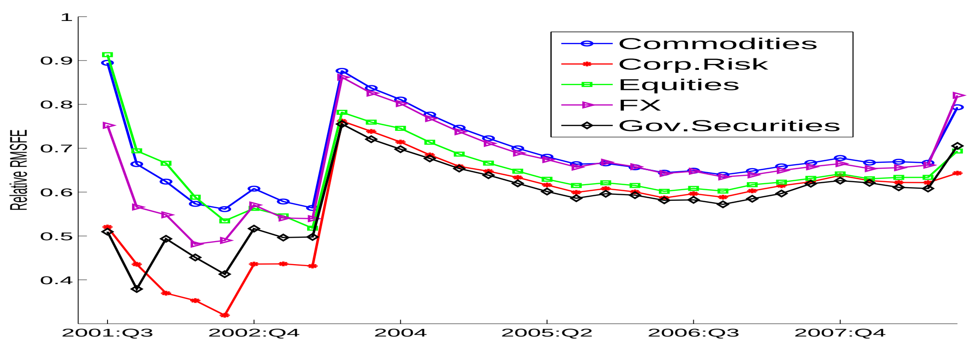


Figure 7: RMSFE of 2DiscMSFE forecast combinations of FADL-MIDAS ($J_X = 2$) for each of the 5 classes of daily financial assets

(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

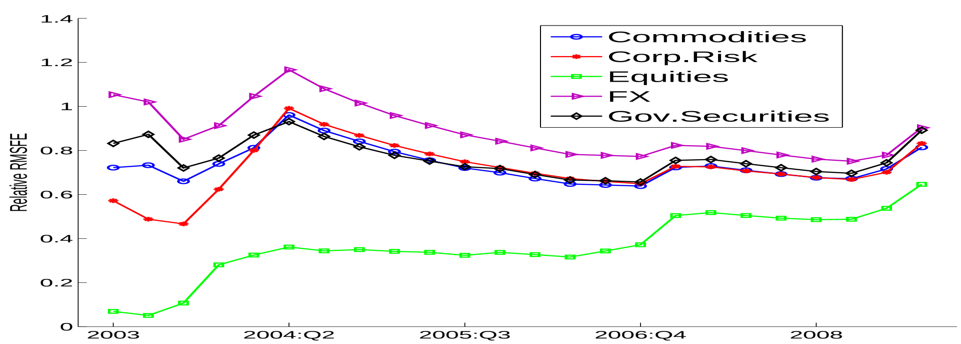
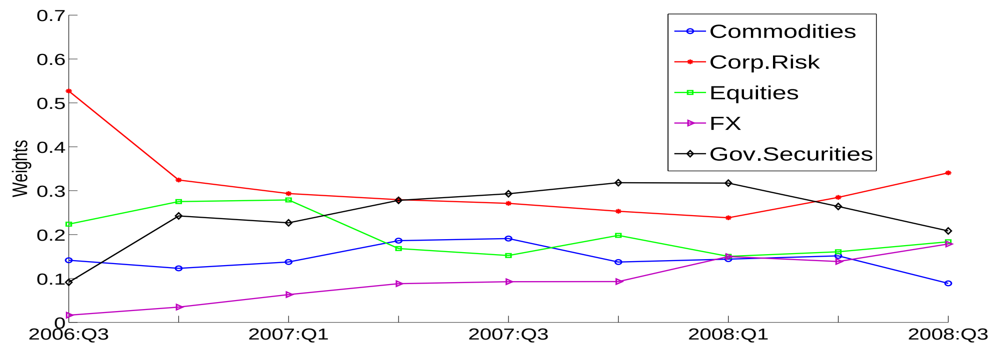
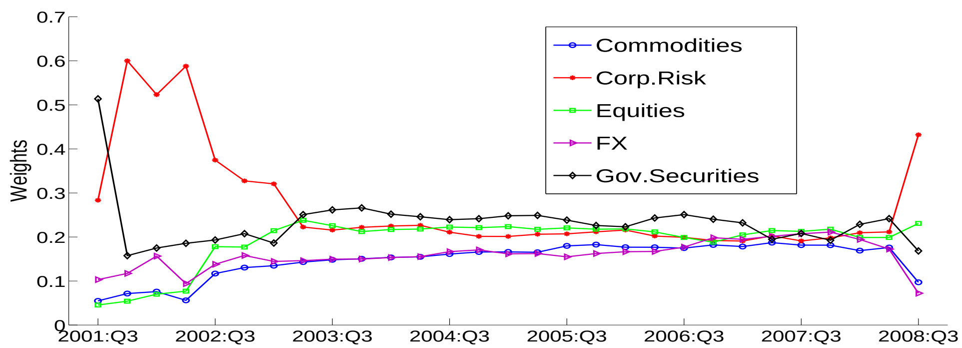


Figure 8: 2DiscMSFE combination weights of FADL-MIDAS ($J_X = 2$) for each of the 5 classes of daily financial assets

(a) Sample of 1999: h = 1



(b) Sample of 1986: h = 1



(c) Sample of 1986: h = 4

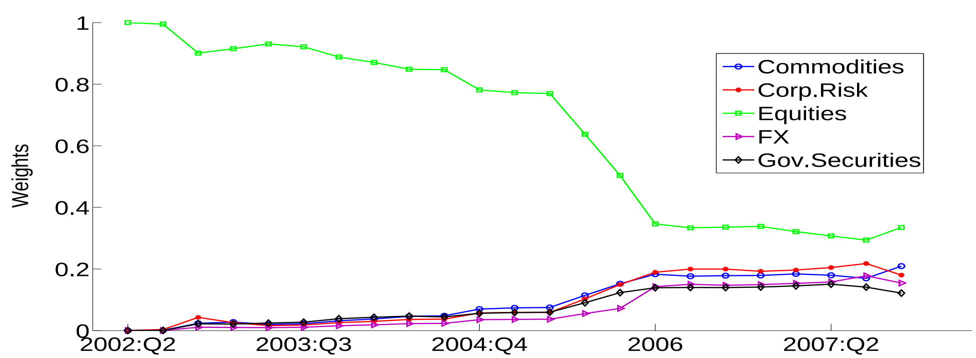
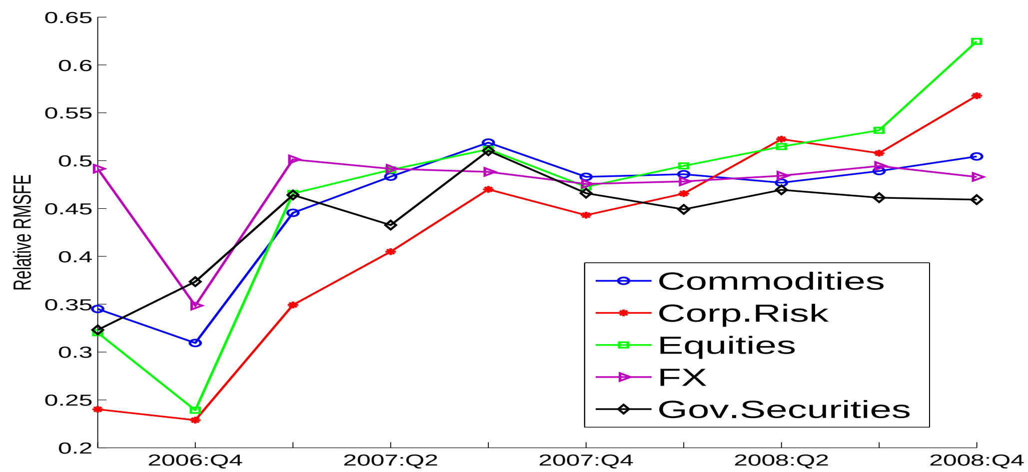


Figure 9: 2DiscMSFE forecast combinations of FADL-MIDAS ($J_X = 2$) for the 5 classes of daily financial factors

(a) RMSFE



(b) Combination weights

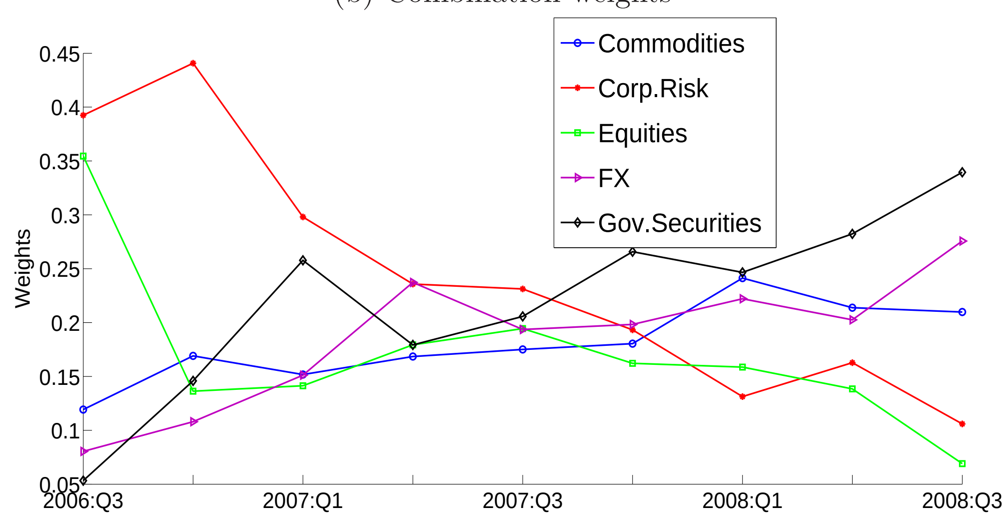


Table 1: Eigenvalues of the daily factors

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 GDP growth relative to the RMSFE of RW for 1-, 2-, and 4-step ahead forecasts for two sample periods: 1999 and 1986. It 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

This table shows 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 (A3). 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-West (DMW), 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					
	DMW	p-val	W	p-val	GW	pval	DMW	p-val	W	p-val	GW	pval	DMW	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 for the 1999 sample

This paper presents the bootstrapped cross-sectional tests of the Mean, Median, and Upper Quartile of the Difference in MSFE and Diebold-Mariano-West tests. For each asset we construct the the Difference in MSFE and the Diebold-Mariano-West statistics. Assuming independence across assets, 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	5.83	0	2.09	0.018	1.82	0.034	4.79	0	5.44	0	1.13	0.448
Median	3.72	0	1.27	0.102	0.27	0.394	3.78	0	3.18	0.001	0.38	0.352
Upper Quartile	3.93	0	7.2	0	4.89	0	3.81	0	5.22	0	3.47	0
ADL vs ADL-MIDAS ($J_X = 2$)												
Mean	7.86	0	2.63	0.004	3.63	0	3.96	0	4.40	0	1.97	0.024
Median	3.43	0	1.34	0.09	2.25	0.012	2.37	0.009	3.19	0.001	0.89	0.187
Upper Quartile	6.91	0	6.17	0	4.46	0	2.17	0.015	5.37	0	2.79	0.003
FADL vs FADL-MIDAS ($J_X = 0$)												
Mean	9.45	0	5.28	0	-0.5	0.691	0.83	0.203	2.39	0.008	1.11	0.456
Median	10.79	0	4.14	0	-0.71	0.761	-0.26	0.603	1.87	0.031	0.81	0.209
Upper Quartile	5.87	0	4.72	0	2.82	0.003	4.36	0	4.76	0	3.28	0
FADL vs FADL-MIDAS ($J_X = 2$)												
Mean	9.06	0	2.59	0.005	0.62	0.268	1.43	0.076	2.11	0.017	1.11	0.133
Median	8.67	0	2.95	0.002	0.32	0.375	-1.75	0.96	1.1	0.136	-1.09	0.862
Upper Quartile	6.66	0	5.37	0	2.88	0.002	1.22	0.111	8.05	0	2.75	0.003
Panel B: Cross-sectional DM												
ADL vs ADL-MIDAS ($J_X = 0$)												
Mean	5.56	0	0.64	0.261	0.71	0.239	5.01	0	4.84	0	0.53	0.298
Median	3.19	0	2.4	0.008	0.47	0.319	5.23	0	3.82	0	0.83	0.203
Upper Quartile	16.36	0	6.27	0	9.15	0	9.32	0	11.16	0	5.11	0
ADL vs ADL-MIDAS ($J_X = 2$)												
Mean	7.60	0	0.99	0.161	2.52	0.006	2.44	0.007	3.67	0	0.56	0.288
Median	7.8	0	1.6	0.055	2.16	0.015	1.65	0.049	3.04	0.001	0.8	0.212
Upper Quartile	21.29	0	7.96	0	15.12	0	8.2	0	4.73	0	4.11	0
FADL vs FADL-MIDAS ($J_X = 0$)												
Mean	12.57	0	4.33	0	-0.32	0.625	-0.13	0.553	1.33	0.092	1.4	0.081
Median	10.58	0	2.68	0.004	-0.35	0.637	-0.29	0.614	1.9	0.029	1.37	0.085
Upper Quartile	20.89	0	8.87	0	3.67	0	3.89	0	7.83	0	6.86	0
FADL vs FADL-MIDAS ($J_X = 2$)												
Mean	10.22	0	2.74	0.003	0.15	0.44	-0.89	0.813	0.73	0.233	-0.39	0.653
Median	10.14	0	3.97	0	0.75	0.227	-1.61	0.946	1.42	0.078	-0.69	0.755
Upper Quartile	19.46	0	4.41	0	5.52	0	2.1	0.018	5.43	0	2.21	0.014

Table 6: HLN Time Series Test for 1986 sample

This table reports p-values for HLN statistic. The statistic corresponds to a one-sided test of the null hypothesis that the forecast given in the column heading encompasses the forecast given in the row heading, i.e. row forecast adds no predictive power to column forecast.

$h = 1$	ALL	COMM	CORP	EQUIT	FX	GOV
ALL		0.05	0.81	0.54	0.08	0.27
COMM	0.95		0.90	0.90	0.16	0.91
CORP	0.13	0.08		0.08	0.10	0.14
EQUIT	0.26	0.08	0.77		0.10	0.17
FX	0.91	0.73	0.88	0.86		0.88
GOV	0.35	0.02	0.62	0.34	0.04	

$h = 2$	ALL	COMM	CORP	EQUIT	FX	GOV
ALL		0.02	0.10	0.57	0.01	0.01
COMM	0.96		0.41	0.71	0.05	0.08
CORP	0.75	0.18		0.63	0.08	0.14
EQUIT	0.11	0.04	0.07		0.01	0.00
FX	0.98	0.92	0.85	0.92		0.68
GOV	0.95	0.64	0.74	0.84	0.04	

$h = 4$	ALL	COMM	CORP	EQUIT	FX	GOV
ALL		0.01	0.02	0.92	0.00	0.00
COMM	0.92		0.21	0.96	0.02	0.06
CORP	0.93	0.54		0.92	0.00	0.03
EQUIT	0.04	0.00	0.01		0.00	0.00
FX	0.97	0.94	0.95	0.95		0.41
GOV	0.99	0.84	0.72	0.98	0.25	

Table 7: Best Daily Financial Assets

This tables shows 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	-	-	-	-

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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 DMW 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,

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

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 DMW test in the case of small samples and the presence of outliers. Both of these features make it an attractive alternative to the DMW 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) and West (1996) 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

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

Then the CW is simply the t-statistic for a zero coefficient that tests that the expected value of d^{adj}_{t+h} 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 DMW 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 $H_0 : E((L(y_{t+h}, \widehat{y}^A_{i,t+h|t}) - L(y_{t+h}, \widehat{y}^B_{j,t+h|t}))|\mathbb{G}_t) = 0$. The GW test statistic is a Wald-type statistic of the following form

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

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 $DMW_{i,h}$ for each asset is $N(0, V_{DMW})$. Assuming independence across assets, we test whether the mean of the DMW statistic for each asset is zero.

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

The distribution of this statistic is bootstrapped with replacement from the asset based empirical distribution of DMW statistics, $\{DMW^*_1, DMW^*_2, ..., DMW^*_N\}$ to compute a bootstrapped p-value. One problem with this test is that it depends on the estimation of the long run variance in $DMW_{i,h}$. 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 bootstrapped cross-sectional test that is simply based on the difference in the MSFE for each asset i, $d_{i,h}$ rather than $DMW_{i,h}$. Another problem with both of these cross-sectional tests is that they focus on the mean. We also employ the bootstrapped 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).