SHOULD MACROECONOMIC FORECASTERS USE HIGH-FREQUENCY FINANCIAL DATA?

Eric Ghysels

University of North Carolina

November 2009
Talk based on:


Jennie Bai, Eric Ghysels & Jonathan Wright (2009) *State Space Models and MIDAS regressions*
Should Macroeconomic Forecasters Use High Frequency Financial Data and How?
Should Macroeconomic Forecasts Use High Frequency Financial Data and How?

YES!!!!!!

The question is: How?
Motivation

- There is a large literature in Finance and Macroeconomics according to which financial variables are forward looking and predictors of economic activity.
Motivation

- There is a large literature in Finance and Macroeconomics according to which financial variables are forward looking and predictors of economic activity.
- However, the empirical evidence is mixed and the results are not robust; see Stock and Watson (2003 *JEL*, 2004, *JFOR*) and Forni et al. (2003, *JME*).
Motivation

- There is a large literature in Finance and Macroeconomics according to which financial variables are forward looking and predictors of economic activity.
- However, the empirical evidence is mixed and the results are not robust; see Stock and Watson (2003 *JEL*, 2004, *JFOR*) and Forni et al. (2003, *JME*).
- These assessments involve quarterly macroeconomic and financial data. They ignore the availability of weekly, daily, intra-daily financial and other series by temporally aggregating all data to the same (low) frequency by computing simple averages.
Over the years we have seen tremendous increase in daily data - in part due to financial innovations. Examples include derivatives, e.g. VIX index, default spreads, implied vols., break-even inflation, etc.
Motivation

- Over the years we have seen tremendous increase in daily data - in part due to financial innovations. Examples include derivatives, e.g. VIX index, default spreads, implied vols., break-even inflation, etc.

- Central bankers look at summary statistics of daily data, charts, plots, etc. Typically such data is used informally.
Motivation

- Over the years we have seen tremendous increase in daily data - in part due to financial innovations. Examples include derivatives, e.g. VIX index, default spreads, implied vols., break-even inflation, etc.
- Central bankers look at summary statistics of daily data, charts, plots, etc. Typically such data is used informally.
- Improving macroeconomic forecasts is of focal interest to academics and policy makers, especially in periods of economic turmoil like the recent financial crisis.
Traditional Approaches to Daily Financial Data

• Aggregate to monthly/quarterly frequency.
Traditional Approaches to Daily Financial Data

- Aggregate to monthly/quarterly frequency.

- Use Kalman filter approach - typically non-trivial to implement.
• We call the regression framework a Mixed Data Sampling regression. MIDAS was introduced in:
We call the regression framework a *Mixed Data Sampling* regression. MIDAS was introduced in:

We call the regression framework a **Mixed Data Sampling** regression. MIDAS was introduced in:

- *regression* context in Forsberg and Ghysels (2005), Ghysels, Santa-Clara and Valkanov (2006), Ghysels, Sinko and Valkanov (2005), Ghysels and Wright (2005), etc.
MIDAS REGRESSIONS

• We call the regression framework a Mixed Data Sampling regression. MIDAS was introduced in:
  • regression context in Forsberg and Ghysels (2005), Ghysels, Santa-Clara and Valkanov (2006), Ghysels, Sinko and Valkanov (2005), Ghysels and Wright (2005), etc.

• A MIDAS regression model involves variables that are of different sampling frequencies and allows for a parsimonious and flexible data-driven weighting scheme.
Recent work showing that one can improve:


OBJECTIVES

- Does the daily information of financial variables improve forecasts of quarterly inflation and output growth?
OBJECTIVES

- Does the daily information of financial variables improve forecasts of quarterly inflation and output growth?

- During a given quarter can we use the flow of the daily financial information to improve/revise our forecasts for the current and future quarters?
OBJECTIVES

• Does the daily information of financial variables improve forecasts of quarterly inflation and output growth?

• During a given quarter can we use the flow of the daily financial information to improve/revise our forecasts for the current and future quarters?

• Do daily factors of a large cross-section help improve forecasts?
CONTRIBUTIONS

- We examine whether new specifications of MIDAS models, which include daily financial series one at a time improve forecasts of benchmark and conventional models of quarterly averages.
We examine whether new specifications of MIDAS models, which include daily financial series one at a time improve forecasts of benchmark and conventional models of quarterly averages.

- We use three approaches:
Contributions

- We examine whether new specifications of MIDAS models, which include daily financial series one at a time improve forecasts of benchmark and conventional models of quarterly averages.

- We use three approaches:
  - Single variable MIDAS regressions.
Contribution

- We examine whether new specifications of MIDAS models, which include daily financial series one at a time improve forecasts of benchmark and conventional models of quarterly averages.

- We use three approaches:
  - Single variable MIDAS regressions.
  - We extract a small set of daily factors from a new dataset that comprises of a cross-section of around 1000 daily financial series during the period 1999-2008. In addition we also use the quarterly S&W quarterly factors with and without financial variables observed at daily frequency.
Contributions

- We examine whether new specifications of MIDAS models, which include daily financial series one at a time improve forecasts of benchmark and conventional models of quarterly averages.

- We use three approaches:
  - Single variable MIDAS regressions.
  - We extract a small set of daily factors from a new dataset that comprises of a cross-section of around 1000 daily financial series during the period 1999-2008. In addition we also use the quarterly S&W quarterly factors with and without financial variables observed at daily frequency.
  - We compute several forecast combination methods and compare the performance of MIDAS models against the conventional approach.
Structure of the Talk

- Aggregation and MIDAS regressions
- ADL-MIDAS regressions
- Kalman filter and MIDAS regressions
- Factor Augmented ADL-MIDAS
- Empirical Analysis
Suppose we want quarterly forecasts of $Y_{t+1}^Q$ of say inflation or GDP growth using - say -oil prices or term spreads that are available daily.

Denote by $X_t^Q$ quarterly average (say this is the aggregation scheme used) of predictor.

Conventional approach, in its simplest form, is an ADL(1,1)

$$Y_{t+1}^Q = \mu + \alpha Y_t^Q + \beta X_t^Q + u_{t+1}$$
AGGREGATION AND MIDAS regressions

- Denote $X^D_{j,t}$, the daily predictor in the $j^{th}$ day in quarter $t$.

- A naive approach would estimate

$$Y_{t+1}^Q = \mu + \alpha Y_t^Q + \sum_{j=1}^{N_D} \beta_j X^D_{j,t} + u_{t+1}$$

where $N_D$ denotes the daily lags or the number of trading days per quarter.

- Problem: Parameter proliferation problem. When $N_D = 66$, we have to estimate 68 slope coefficients!
ADL-MIDAS models

• A MIDAS approach would estimate

\[ ADL - MIDAS(1, k_X^D): \]

\[ Y_{t+1}^Q = \mu + \alpha Y_t^Q + \beta \sum_{j=0}^{k_X^D-1} \sum_{i=1}^{N_D} w_{i+j*k_X^D}(\theta^D) X_{i,t-j}^D + u_{t+1} \]

• Note that the number of daily lags is a multiple of the number of trading days in a quarter, \( N_D \).

• This leads to notation very similar to ARMA models, e.g. ADL-MIDAS(1,1) or ADL-MIDAS(AIC,AIC).
Here we employ a two parameter Exponential Almon lag polynomial

\[ w_j(\theta) \sim \exp(\theta_1 j + \theta_2 j^2) \]

An alternative parameterization is based on Beta distribution: \( \theta = (\theta_1, \theta_2) \):

\[ w_j(\theta) \sim \text{Beta}(\theta_1, \theta_2) \]
Alternative weighting schemes of the exponential Almon polynomial

- Flat(0,0)
- Near Flat (0.0001,0.0001)
- Fast Decay(0.0007,-0.05)
- Slow Decay(0.0007,-0.006)
- Increasing(0.1,0.001)
- Bell shaped(0.07,-0.0018)
**Decomposing ADL-MIDAS(1,1)**

- Consider the following decomposition of the ADL-MIDAS(1,1) model in the context of temporal aggregation

\[
Y_{t+1}^Q = \mu + \alpha Y_t^Q + \beta X_t^Q + \beta Z_t^D(\theta_X^D) + u_{t+1}
\]

where

\[
X_t^Q \equiv (X_{1,t}^D + X_{2,t}^D + \ldots + X_{N_D,t}^D)/N_D
\]

and \(Z_t^D(\theta_X^D)\) is the omitted component from the ADL

\[
Z_t^D(\theta_X^D) = \sum_{i=0}^{N_D-1} (w_i(\theta_X^D) - 1/N_D) \Delta^{N_D-i} X_{i-(j-1),t}^D
\]
The weighting scheme or the shape of the polynomial determines the temporal features of the omitted variable.

Using this decomposition Andreou, Ghysels, and Kourtellos (2009, *JoE*) show that

1. Flat Aggregation yields asymptotically inefficient estimators even in the simplest case where the high frequency process is an *i.i.d*.

2. Temporal aggregation using equal weights results in inconsistent slope estimates when the high frequency process is for an instance an AR.
Here, in the context of forecasting, does the loss of information imposed by flat aggregation have any consequences? Yes!

A small Monte Carlo compares the finite sample performance of ADL-MIDAS against the conventional ADL.

<table>
<thead>
<tr>
<th>Aggregation Horizon</th>
<th>3</th>
<th>40</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>n=100</td>
<td>1.018</td>
<td>0.974</td>
<td>0.973</td>
</tr>
<tr>
<td>n=200</td>
<td>1.000</td>
<td>0.968</td>
<td>0.951</td>
</tr>
</tbody>
</table>

RMSFE of ADL-MIDAS relative to ADL

\[ X_t \sim i.i.d. \quad X_t \sim AR(1) \]

\[ \rho = 0.9 \]
WHAT ABOUT THE Kalman FILTER?

• The mismatch of sampling frequency has been address using state space models by Harvey and Pierse (1984), Zadrozny (1990), Bernanke, Gertler and Watson (1997), Mariano and Murasawa (2003), Mittnik and Zadrozny (2004), Aruoba, Diebold and Scotti (2009), Ghysels and Wright (2009), Kuzin, Marcellino and Schumacher (2009), among others.
What about the Kalman filter?

• The mismatch of sampling frequency has been address using state space models by Harvey and Pierse (1984), Zadrozny (1990), Bernanke, Gertler and Watson (1997), Mariano and Murasawa (2003), Mittnik and Zadrozny (2004), Aruoba, Diebold and Scotti (2009), Ghysels and Wright (2009), Kuzin, Marcellino and Schumacher (2009), among others.

• Treats the low frequency data as “missing data”. Kalman filter is convenient computational device to extract missing data points.
What about the Kalman filter?

• The mismatch of sampling frequency has been address using state space models by Harvey and Pierse (1984), Zadrozny (1990), Bernanke, Gertler and Watson (1997), Mariano and Murasawa (2003), Mittnik and Zadrozny (2004), Aruoba, Diebold and Scotti (2009), Ghysels and Wright (2009), Kuzin, Marcellino and Schumacher (2009), among others.

• Treats the low frequency data as “missing data”. Kalman filter is convenient computational device to extract missing data points.

• We will show that MIDAS regressions mimic Kalman filter, without having to specify a full parametric specification of a state space model.
Consider single factor state space model written as (using slightly different notation - $t - j/m$):

$$x_{t-j/m} = f_{t-j/m} + v^x_{t-j/m}$$

for $j \neq k \times m$, $k \in \mathbb{N}$

$$\begin{pmatrix} x_{t-j/m} \\ y_{t-j/m} \end{pmatrix} = \begin{pmatrix} 1 \\ b \end{pmatrix} f_{t-j/m} + \begin{pmatrix} v^x_{t-j/m} \\ v^y_{t-j/m} \end{pmatrix}$$

for $j = k \times m$

where the transition equation is

$$f_t = \rho f_{t-1/m} + \varepsilon_t$$
• Using only past HF data yields exact MIDAS regression (with exponential Almon lags):

\[ E(y_{t+1} | I_t^{HF}) = b\kappa \sum_{j=0}^{\infty} (\rho - \kappa)^j x_{t-j/m} \]

with \( w_j(\theta) \sim \exp(\theta j) \). Hence, \( \theta \sim (\rho - \kappa) \), where \( \kappa \) is steady state Kalman gain.

• Note that MIDAS regression does not identify \( \rho \) or \( \kappa \) or for that matter the parameters determining \( \kappa \).
State Space Models and MIDAS

- Using both low and high frequency past data - $I_t^M$ information set:

\[
E \left[ y_{t+1} \mid I_t^M \right] = \rho^3 \kappa_{3,1} \sum_{j=0}^{\infty} \varphi^j y_{t-j} + \rho^3 \sum_{j=0}^{\infty} \varphi^j x(\theta_x)_{t-j}
\]

where

\[
x(\theta_x)_t \equiv [\kappa_{3,2} + (\rho - \rho \kappa_3) \kappa_2 L^{1/3} + (\rho - \rho \kappa_3)(\rho - \rho \kappa_2) \kappa_1 L^{2/3}] x_t
\]

- The above equation relates to the multiplicative MIDAS regression models discussed later.
The state space model approach has many benefits, but also some drawbacks.

State space models require to explicitly specify a linear dynamic model with Gaussian errors for all the series involved - high frequency data series, latent high frequency series treated as missing and the low frequency observed processes.

Even when MIDAS polynomial is only approximate - it is a good approximation (more later).
MULTIPlicative MIDAS regressions

- Define the following filtered parameter-driven variable

\[ X_t^Q(\theta^D_X) \equiv \sum_{i=1}^{N_D} w_i(\theta^D_X) X_{i,t}^D \]

- \( ADL - MIDAS - M(p_Y^Q, p_X^Q) \):

\[ Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_X^Q-1} \beta_k X_{t-k}^Q(\theta^D_X) + u_{t+1} \]

- The weighting scheme in \( ADL - MIDAS \) corresponds to the structure of a steady state Kalman filter. By hyper-parameterizing the slope coefficients of the filtered variable, \( X_t^Q(\theta^D_X) \) using another MIDAS polynomial we get the following restricted \( ADL - MIDAS - M \)

- For a similar idea see also Chen and Ghysels (2008).
Daily Weights of ADL-MIDAS-M(AIC,AIC) and ADL(AIC,AIC) for forecasting CPI core inflation using the daily predictor 1month A2P2F2 Non Fin. CP - AA Fin. CP Spread
Kalman vs MIDAS: Parsimony and Computational Complexity

- State space models are typically computationally involved and require a system-based specification.

- MIDAS regressions are reduced form approximations less prone to specification errors, parsimonious and computationally simple (it is not difficult to deal with hundreds of daily series).
Approximation Errors: Regular MIDAS and One-Factor State Space Model - Two Quarters ahead

<table>
<thead>
<tr>
<th>$d$ and $\rho$</th>
<th>0.5</th>
<th>0.9</th>
<th>0.9</th>
<th>0.5</th>
<th>0.9</th>
<th>0.95</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>0.9</td>
<td>0.01</td>
<td>0.07</td>
<td>0.08</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>0.95</td>
<td>0.00</td>
<td>0.13</td>
<td>0.14</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>
### Specification Errors 2-factor models: Regular MIDAS and One-Factor State Space Model - Two Quarters ahead

<table>
<thead>
<tr>
<th>$d$ and $\rho$</th>
<th>0.5</th>
<th>0.9</th>
<th>0.95</th>
<th>0.99</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>0.75</td>
<td>0.91</td>
<td>0.96</td>
<td>1.00</td>
</tr>
<tr>
<td>0.9</td>
<td>0.66</td>
<td>0.92</td>
<td>1.03</td>
<td>1.17</td>
</tr>
<tr>
<td>0.95</td>
<td>0.65</td>
<td>0.90</td>
<td>1.06</td>
<td>1.25</td>
</tr>
<tr>
<td>0.99</td>
<td>0.64</td>
<td>0.82</td>
<td>0.98</td>
<td>1.35</td>
</tr>
</tbody>
</table>
Quarterly Factor Augmented ADL-MIDAS

- Recently, Forni, Hallin, Lippi, and Reichlin (2000, 2001, 2003), Stock and Watson (2002a,b), Bai and Ng (2002) and Bai (2003), among many others, have developed factor model techniques that are tailored to exploit a large cross-sectional dimension.

- We augment the aforementioned MIDAS models with quarterly factors, $F_t$, obtained by following dynamic factor model

\[ X_t = \Lambda_t F_t + u_t \]  
\[ F_t = \Phi F_{t-1} + \eta_t \]  
\[ u_{it} = a_{it}(L)u_{it-1} + \varepsilon_{it}, \quad i = 1, 2, ..., n. \]

- The number of factors are chosen based on the information criteria proposed by Bai and Ng (2002).
Factor Augmented ADL-MIDAS (cont’d)

- Augmenting ADL-MIDAS with Factor yields the FADL – MIDAS\((p_Y^Q, p_F^Q, k_X^D)\):

\[ Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_F^Q-1} \beta_k F_{t-k}^Q + \gamma \sum_{j=0}^{k_X^D-1} \sum_{i=1}^{N_D} w_{i+j*\kappa_X^D}(\theta^D) X_{i,t-j}^D + u_{t+1} \]

- Similarly, augmenting the ADL-MIDAS-M with Factor yields the FADL – MIDAS – M\((p_Y^Q, p_F^Q, p_X^Q)\).
STRUCTURE OF THE EMPIRICS

- Data
- Quarterly Factors
- Daily Factors
- Univariate Benchmark Models
- No leads versus leads (nowcasting)
DATA

• We forecast the US quarterly inflation rate and the growth rate of economic activity using various measures.
• For inflation we use four different measures: CPI-all, CPI-core, PCE-all, PCE-core.
• For economic activity we use Industrial Production (IP) and quarterly Real Gross Domestic Product (RGDP).
• We use two sample periods of US data for the post great moderation period: 1984:Q1-2008:Q4 (T=100) and 1999:Q1-2008:Q4 (T=40).
• The two subperiods involve different numbers, N, of daily financial predictors due to daily data availability.
Here, we present the results of the shorter, which includes a larger cross-section of daily financial series.

Our analysis of the sample of 1999 considers two sets of databases of different sampling frequencies of macroeconomic and financial indicators.

1. The S&W quarterly dataset of 69 quarterly series of real output and income, capacity utilization, employment and hours, price indices, money e.t.c. This dataset excludes variables observed at the daily frequency and included in the daily dataset.
2. A daily dataset with large cross-section of 988 daily series for the recent period of 1999-2008 and a relative smaller cross-section of for five categories of financial assets as well as the ADS Index.
Using these datasets we do the following things:

1. Extract quarterly factors
2. Extract daily factors
3. Investigate the predictive ability of single series subset of the 988 predictors (90 variables) that have been proposed in the literature as the most important predictors for inflation and economic activity.
4. Pool predictors (the 988) in asset classes and see how well combinations among a given asset class perform.
DATA: DAILY MACRO AND FINANCIAL INDICATORS

- **Commodities** (241): US individual commodity prices, commodity indices and futures.

- **Corporate Risk** (210): yields such as bonds for various maturities, libor, Certificate of Deposits, Eurodollars, Commercial Paper, default spreads using matched maturities, quality spreads, and other short term spreads such as TED.

- **Equities** (219): 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.
Data: daily macro and financial indicators

- **Government Securities** (248): government treasury bonds rates and yields, term spreads, TIPS yields, break-even inflation.

- **Foreign Exchange Rates** (70): trading partners in the broad index as well as international currency rates of major indices and effective exchange rate indices.
**DATA: RMSFE**

We provide pseudo out-of-sample forecasts based on a recursive estimation method and evaluate the predictive ability of our models for various forecasting horizons $h = 1, 2, 4$ using the recursive RMSFE

$$RMSFE_{i,t} = \sqrt{\frac{1}{t - T_0 + 1} \sum_{\tau = T_0}^{t} (y_{\tau+h}^h - \hat{y}_{i,\tau+h|\tau}^h)^2},$$

where $t = T_1, \ldots, T_2$. $T_0$ is the point at which the first individual pseudo out-of-sample forecast is computed. Note that in our case

$$
T_0 = 2006 : Q1 \\
T_1 = 2006 : Q1 + h \\
T_2 = 2008 : Q4 - h
$$
Quarterly Factor Analysis

- Non-stationary series were transformed by taking first differences or first log differences.

- In the case of quarterly factors ICP criteria suggest the choice of the first two factors. This result is consistent with the finding of Stock and Watson (2008).
  
  - $F_{1Q}$ and $F_{2Q}$ explain 36% and 12%, respectively, of the total variation in the panel.
  - $F_{1Q}$ correlates highly with IP & Purchasing Manager’s Index.
  - $F_{2Q}$ correlates highly with Employment, NAPM Inventories Index.

-Interestingly, we find that our first two quarterly factors are the same as the corresponding S&W factors, which were extracted from a dataset which included 20 extra daily series.
Daily Financial Factors 1999-2008

- In the case of daily factors ICP criteria are not helpful as they always suggest 10 factors. Therefore, we investigate all 10 daily factors one at a time.

<table>
<thead>
<tr>
<th>Daily Factors</th>
<th>% Total Variation</th>
<th>% of Explained Variation Within Each Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>COMM</td>
</tr>
<tr>
<td>$F^D_1$</td>
<td>0.29</td>
<td>0.01</td>
</tr>
<tr>
<td>$F^D_2$</td>
<td>0.17</td>
<td>0.04</td>
</tr>
<tr>
<td>$F^D_3$</td>
<td>0.14</td>
<td>0.17</td>
</tr>
<tr>
<td>$F^D_4$</td>
<td>0.11</td>
<td>0.64</td>
</tr>
<tr>
<td>$F^D_5$</td>
<td>0.09</td>
<td>0.22</td>
</tr>
<tr>
<td>$F^D_6$</td>
<td>0.07</td>
<td>0.59</td>
</tr>
<tr>
<td>$F^D_7$</td>
<td>0.04</td>
<td>0.34</td>
</tr>
<tr>
<td>$F^D_8$</td>
<td>0.03</td>
<td>0.07</td>
</tr>
<tr>
<td>$F^D_9$</td>
<td>0.03</td>
<td>0.12</td>
</tr>
<tr>
<td>$F^D_{10}$</td>
<td>0.02</td>
<td>0.12</td>
</tr>
</tbody>
</table>
First Daily Financial Factor during 1999-2008

Daily Sample Period 1/1/1999 - 31/12/2008
Second Daily Financial Factor during 1999-2008

Daily Sample Period 1/1/1999 - 31/12/2008
Third Daily Financial Factor during 1999-2008

Daily Sample Period 1/1/1999 - 31/12/2008
Univariate Benchmark Models

Benchmark Models for Inflation

AO: \( \pi_{t+4}^Q = \pi_t^Q + u_{t+4} \)

UCSV: \( \pi_t^Q = \tau_t + u_t \), where \( \tau_t = \tau_{t-1} + e_t \),
\( u_t = \sigma_{u,t} \eta_{u,t} \) and \( e_t = \sigma_{e,t} \eta_{e,t} \),
\( \ln \sigma_{u,t}^2 = \ln \sigma_{u,t-1}^2 + \nu_{u,t}, \) and \( \ln \sigma_{e,t}^2 = \ln \sigma_{e,t-1}^2 + \nu_{e,t}, \)
\( \eta_t = (\eta_{u,t}, \eta_{e,t}) \) is \( i.i.d. N(0, I_2) \),
\( \nu_t = (\nu_{u,t}, \nu_{e,t}) \) is \( i.i.d. N(0, \gamma I_2) \), and
\( \eta_t \) and \( \nu_t \) are independent, \( \gamma \) is a scalar.

Benchmark Model for Growth

RW: \( Y_{t+h}^h = \mu + e_{t+h} \)
ONE AT A TIME ANALYSIS

- We investigate the predictive ability of the daily financial indicators one at a time by comparing the performance of ADL-MIDAS and FADL-MIDAS against the conventional ADL and FADL as well as the benchmark models for inflation and growth rates.

- For this analysis we consider 90 daily variables (a subset of the 988 predictors) that have been proposed in the literature as the most important predictors of inflation and economic activity from each of the five categories.
ONE AT A TIME ANALYSIS

- We investigate the predictive ability of the daily financial indicators one at a time by comparing the performance of ADL-MIDAS and FADL-MIDAS against the conventional ADL and FADL as well as the benchmark models for inflation and growth rates.

- For this analysis we consider 90 daily variables (a subset of the 988 predictors) that have been proposed in the literature as the most important predictors of inflation and economic activity from each of the five categories.
**Best Models: RMSFE relative to the benchmark - No Leads**

<table>
<thead>
<tr>
<th>Horizon</th>
<th>CPIall Inf</th>
<th>GDP Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 4</td>
<td>1 4</td>
</tr>
<tr>
<td>UCSV</td>
<td>4.28 1.44</td>
<td>-</td>
</tr>
<tr>
<td>AO</td>
<td>6.79 1.85</td>
<td>-</td>
</tr>
<tr>
<td>RW</td>
<td>- -</td>
<td>3.35 1.69</td>
</tr>
<tr>
<td>AR</td>
<td>1.04 1.17</td>
<td>0.96 1.03</td>
</tr>
<tr>
<td>FAR</td>
<td>1.02 1.48</td>
<td>0.69 0.77</td>
</tr>
<tr>
<td>ADL</td>
<td>0.57 0.73</td>
<td>0.59 0.31</td>
</tr>
<tr>
<td>FADL</td>
<td>0.59 1.01</td>
<td>0.37 0.44</td>
</tr>
<tr>
<td>ADL-MIDAS</td>
<td>0.43 0.44</td>
<td>0.48 0.30</td>
</tr>
<tr>
<td>FADL-MIDAS</td>
<td>0.47 0.72</td>
<td>0.36 0.28</td>
</tr>
</tbody>
</table>
## CPI: Best Models - No Leads

<table>
<thead>
<tr>
<th>Rank</th>
<th>Specification</th>
<th>Predictor</th>
<th>Rel MSFE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Forecast Horizon (h=1)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>ADL-MIDAS(4,1)</td>
<td>Platinum</td>
<td>0.43</td>
</tr>
<tr>
<td>2</td>
<td>ADL-MIDAS(4,3)</td>
<td>Platinum</td>
<td>0.43</td>
</tr>
<tr>
<td>3</td>
<td>ADL-MIDAS(4,4)</td>
<td>Platinum</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td><strong>Forecast Horizon (h=4)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>ADL-MIDAS-M(AIC,AIC)</td>
<td>1M A2P2F2 Non Fin - 1M AA Non Fin CP</td>
<td>0.44</td>
</tr>
<tr>
<td>2</td>
<td>ADL-MIDAS-M(AIC,AIC)</td>
<td>1M A2P2F2 Non Fin - 1M AA Fin CP</td>
<td>0.53</td>
</tr>
<tr>
<td>3</td>
<td>ADL-MIDAS-M(AIC,AIC)</td>
<td>1Y LIBOR</td>
<td>0.70</td>
</tr>
</tbody>
</table>
**CPIall: The next best three predictors - NOLEADS**

<table>
<thead>
<tr>
<th>Rank</th>
<th>Specification</th>
<th>Predictor</th>
<th>Rel MSFE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Forecast Horizon (h=1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>32</td>
<td>ADL(1,3)</td>
<td>Reuters/Jeffries CRB Index</td>
<td>0.68</td>
</tr>
<tr>
<td>69</td>
<td>FADL(4,1,4)</td>
<td>3M Treasury Bill</td>
<td>0.79</td>
</tr>
<tr>
<td>70</td>
<td>ADL(AIC,AIC)</td>
<td>WTI Oil Future</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>Forecast Horizon (h=4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>ADL-MIDAS-M(AIC,AIC)</td>
<td>1M A2P2F2 Non Fin - 1M AA Fin CP</td>
<td>0.53</td>
</tr>
<tr>
<td>3</td>
<td>ADL-MIDAS-M(AIC,AIC)</td>
<td>1Y LIBOR</td>
<td>0.70</td>
</tr>
<tr>
<td>5</td>
<td>ADL(4,4)</td>
<td>UK$/US$</td>
<td>0.73</td>
</tr>
</tbody>
</table>
### GDP Growth: Best Models - NoLeads

<table>
<thead>
<tr>
<th>Rank</th>
<th>Specification</th>
<th>Predictor</th>
<th>Rel MSFE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Forecast Horizon (h=1)</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>FADL-MIDAS(4,1,4)</td>
<td>Canadian$/US$</td>
<td>0.36</td>
</tr>
<tr>
<td>2</td>
<td>FADL(4,1,4)</td>
<td>Canadian$/US$</td>
<td>0.37</td>
</tr>
<tr>
<td>3</td>
<td>FADL(AIC,1,AIC)</td>
<td>Canadian$/US$</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Forecast Horizon (h=4)</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>FADL-MIDAS(4,1,1)</td>
<td>1M A2P2F2 Non Fin - 1M AA Fin CP</td>
<td>0.28</td>
</tr>
<tr>
<td>2</td>
<td>ADL-MIDAS(4[r],1)</td>
<td>1M Eurodollar-Fed Funds</td>
<td>0.30</td>
</tr>
<tr>
<td>3</td>
<td>ADL(4,4)</td>
<td>Lead Forward</td>
<td>0.31</td>
</tr>
</tbody>
</table>
## GDP growth: The next best three predictors - noleads

<table>
<thead>
<tr>
<th>Rank</th>
<th>Specification</th>
<th>Predictor</th>
<th>Rel MSFE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Forecast Horizon (h=1)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>ADL-MIDAS(4[r],4)</td>
<td>ADS</td>
<td>0.48</td>
</tr>
<tr>
<td>10</td>
<td>FADL-MIDAS-M(AIC,1,AIC)</td>
<td>1M LIBOR</td>
<td>0.49</td>
</tr>
<tr>
<td>11</td>
<td>FADL-MIDAS(4,1,1)</td>
<td>1Y Treasury Bill - Fed Funds</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td><strong>Forecast Horizon (h=4)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>ADL-MIDAS(4[r],1)</td>
<td>1M Eurodollar - Fed Funds</td>
<td>0.30</td>
</tr>
<tr>
<td>3</td>
<td>ADL(4,4)</td>
<td>Lead Forward</td>
<td>0.31</td>
</tr>
<tr>
<td>6</td>
<td>FADL-MIDAS(4,1,1)</td>
<td>1M A2P2F2 Non Fin - 1M AA Non Fin CP</td>
<td>0.34</td>
</tr>
</tbody>
</table>
Giannone et al (2008), among others, have formalized the process of updating the nowcast and forecasts as new releases of data become available.
Giannone et al (2008), among others, have formalized the process of updating the nowcast and forecasts as new releases of data become available.

MIDAS regression models with *leads* mimics this process by incorporating real-time information available mainly on the daily financial variables.
Giannone et al (2008), among others, have formalized the process of updating the nowcast and forecasts as new releases of data become available.

MIDAS regression models with *leads* mimics this process by incorporating real-time information available mainly on the daily financial variables.

Suppose our objective is to forecast quarterly economic activity or inflation and we stand on the first day of the last month of the quarter.
Giannone et al (2008), among others, have formalized the process of updating the nowcast and forecasts as new releases of data become available.

MIDAS regression models with leads mimics this process by incorporating real-time information available mainly on the daily financial variables.

Suppose our objective is to forecast quarterly economic activity or inflation and we stand on the first day of the last month of the quarter.

This means that if we wish to make a forecast for the current quarter we could use up to 44 leads of daily data for financial markets that trade on weekdays.
Consider the $FADL - MIDAS$, which allows for $J_D^X$ daily leads for the daily predictor, expressed in multiples of months.
Consider the $FADL$ – $MIDAS$, which allows for $J_D^X$ daily leads for the daily predictor, expressed in multiples of months.

Then we can specify the $FADL$ – $MIDAS(p_Y^Q, p_F^Q, p_X^Q, J_X^D)$ model:

$$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \alpha_k Y_{t-k}^Q + \sum_{k=0}^{p_F^Q-1} \beta_k F_{t-k}^Q + \gamma \sum_{j=0}^{k_X^D-1} \sum_{i=1}^{N_D} w_{i+j* k_X^D} (\theta_D^X) X_{i+J_X^D, t-j}^D + u_{t+1}$$
**Median Forecast Combinations across blocks of assets for PCE Core Inflation, \( h = 4 \)**

<table>
<thead>
<tr>
<th></th>
<th>( F^D )</th>
<th>ALL</th>
<th>COMM</th>
<th>CORP</th>
<th>EQT</th>
<th>FX</th>
<th>GOV</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADL</td>
<td>0.41</td>
<td>1.00</td>
<td>1.02</td>
<td>1.05</td>
<td>0.92</td>
<td>1.29</td>
<td>1.10</td>
</tr>
<tr>
<td>FADL</td>
<td>0.38</td>
<td>1.36</td>
<td>1.44</td>
<td>1.45</td>
<td>0.84</td>
<td>1.33</td>
<td>1.59</td>
</tr>
<tr>
<td>ADL-MIDAS (no leads)</td>
<td>0.41</td>
<td>0.79</td>
<td>0.81</td>
<td>0.96</td>
<td>0.80</td>
<td>0.96</td>
<td>0.87</td>
</tr>
<tr>
<td>FADL-MIDAS (no leads)</td>
<td>0.48</td>
<td>1.00</td>
<td>1.06</td>
<td>1.30</td>
<td>0.81</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>ADL-MIDAS (leads)</td>
<td>0.29</td>
<td>0.83</td>
<td>0.88</td>
<td>0.85</td>
<td>0.80</td>
<td>0.90</td>
<td>0.94</td>
</tr>
<tr>
<td>FADL-MIDAS (leads)</td>
<td>0.38</td>
<td>1.17</td>
<td>1.16</td>
<td>1.22</td>
<td>1.12</td>
<td>1.16</td>
<td>1.33</td>
</tr>
</tbody>
</table>
## Median Forecast Combinations Across Blocks of Assets for IP, h = 1

<table>
<thead>
<tr>
<th></th>
<th>$F^D$</th>
<th>ALL</th>
<th>COMM</th>
<th>CORP</th>
<th>EQT</th>
<th>FX</th>
<th>GOV</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADL</td>
<td>0.44</td>
<td>0.60</td>
<td>0.61</td>
<td>0.59</td>
<td>0.58</td>
<td>0.60</td>
<td>0.67</td>
</tr>
<tr>
<td>FADL</td>
<td>0.41</td>
<td>0.54</td>
<td>0.55</td>
<td>0.54</td>
<td>0.53</td>
<td>0.52</td>
<td>0.57</td>
</tr>
<tr>
<td>ADL-MIDAS (no leads)</td>
<td>0.39</td>
<td>0.61</td>
<td>0.62</td>
<td>0.58</td>
<td>0.57</td>
<td>0.61</td>
<td>0.65</td>
</tr>
<tr>
<td>FADL-MIDAS (no leads)</td>
<td>0.43</td>
<td>0.54</td>
<td>0.56</td>
<td>0.53</td>
<td>0.50</td>
<td>0.54</td>
<td>0.56</td>
</tr>
<tr>
<td>ADL-MIDAS (leads)</td>
<td>0.36</td>
<td>0.45</td>
<td>0.46</td>
<td>0.41</td>
<td>0.44</td>
<td>0.47</td>
<td>0.48</td>
</tr>
<tr>
<td>FADL-MIDAS (leads)</td>
<td>0.36</td>
<td>0.44</td>
<td>0.44</td>
<td>0.41</td>
<td>0.42</td>
<td>0.46</td>
<td>0.49</td>
</tr>
</tbody>
</table>
Conclusion

- There are substantial forecasting gains for forecasting inflation and economic activity using higher frequency/daily financial data and (F)ADL-MIDAS models
CONCLUSION

- There are substantial forecasting gains for forecasting inflation and economic activity using higher frequency/daily financial data and (F)ADL-MIDAS models.

- (F)ADL-MIDAS models improve the forecasts of the benchmarks substantially:
CONCLUSION

• There are substantial forecasting gains for forecasting inflation and economic activity using higher frequency/daily financial data and (F)ADL-MIDAS models

• (F)ADL-MIDAS models improve the forecasts of the benchmarks substantially:
  • For CPI inflation by about 55% of the RMSFE of the UCSV for both 1 and 4 quarters ahead,
CONCLUSION

• There are substantial forecasting gains for forecasting inflation and economic activity using higher frequency/daily financial data and (F)ADL-MIDAS models

• (F)ADL-MIDAS models improve the forecasts of the benchmarks substantially:
  • For CPI inflation by about 55% of the RMSFE of the UCSV for both 1 and 4 quarters ahead,
  • For IP by about 70% and 55% of the RMSFE of the RW for 1 and 4 quarters ahead, respectively,
CONCLUSION

- There are substantial forecasting gains for forecasting inflation and economic activity using higher frequency/daily financial data and (F)ADL-MIDAS models.

- (F)ADL-MIDAS models improve the forecasts of the benchmarks substantially:
  - For CPI inflation by about 55% of the RMSFE of the UCSV for both 1 and 4 quarters ahead,
  - For IP by about 70% and 55% of the RMSFE of the RW for 1 and 4 quarters ahead, respectively,
  - For GDP growth by about 65% and 70% of the RMSFE of the RW benchmark models, respectively, for both 1 and 4 quarters ahead.
• ADL-MIDAS and FADL-MIDAS models improve the forecasts of conventional ADL models, which are based on flat aggregation. For instance, in the case of CPI Inflation the best ADL-MIDAS improves the accuracy of the best ADL by about 30%.
CONCLUSION

- ADL-MIDAS and FADL-MIDAS models improve the forecasts of conventional ADL models, which are based on flat aggregation. For instance, in the case of CPI Inflation the best ADL-MIDAS improves the accuracy of the best ADL by about 30%.

- MIDAS models can efficiently incorporate information from daily factors.
Conclusion

- ADL-MIDAS and FADL-MIDAS models improve the forecasts of conventional ADL models, which are based on flat aggregation. For instance, in the case of CPI Inflation the best ADL-MIDAS improves the accuracy of the best ADL by about 30%.

- MIDAS models can efficiently incorporate information from daily factors.

- MIDAS models can incorporate real-time information and provide more accurate forecasts of the current and future quarters.
CONCLUSION

• The set of best predictors varies from variable to variable and forecast horizon. Overall, this set of best predictors includes:
CONCLUSION

- The set of best predictors varies from variable to variable and forecast horizon. Overall, this set of best predictors includes:
  - For CPI Inflation, (i) Commodities (Platinum, Sugar, WTI Oil Future, Lead Forward, Corn Future, Oat); (ii) Corporate Risk (spread of A2P2F2 with AA Fin CP or AA Non Fin CP, LIBOR, Break-even inflation); (iii) Government Securities (3 Month T-Bill); Foreign Exchange Rates (FXUK, EFXbroad);
CONCLUSION

• The set of best predictors varies from variable to variable and forecast horizon. Overall, this set of best predictors includes:

  • For CPI Inflation, (i) Commodities (Platinum, Sugar, WTI Oil Future, Lead Forward, Corn Future, Oat); (ii) Corporate Risk (spread of A2P2F2 with AA Fin CP or AA Non Fin CP, LIBOR, Break-even inflation); (iii) Government Securities (3 Month T-Bill); Foreign Exchange Rates (FXUK, EFXbroad);

  • For GDP growth, (i) Foreign Exchange Rates (Canadian$/US$); (ii) Corporate Risk (spread of A2P2F2 with AA Fin CP or AA Non Fin CP, Eurodollar-Fed Funds LIBOR, Break-even Inflation, Merrill Lynch A - 10Y TBond, Merrill Lynch AA - 10Y TBond); (iii) Government Securities (1Y T-Bond - Fed Funds); (iv) ADS.
THANKS!
THANKS!

STILL A LOT OF WORK TO DO!