Forecasting the European GDP using the (MI)xed (DA)ta (S)ampling models: The key role of the Consumption Sentiment Leading Indicator.

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Importance of High-frequency Information

Traditional models consider the <u>same</u> sampling (low) frequency

<u>Example</u>: <u>Quarterly</u> GDP growth vs <u>monthly</u> employment (EMP) and <u>weekly</u> stock prices (STOCK)

- average/sum of monthly EMP data within each quarter
- last weekly STOCK price within each quarter

<u>Simple, but</u>

- Loss of information
- Dynamics of the aggregate model ≠ dynamics in high or mixed frequency (Ghysels and Marcellino, 2018)

→ Use the MIDAS models

MIDAS Models – Literature

- **Introduced** by Ghysels, Santa-Clara, and Valkanov (2004)
- **Solution** to **equal weighting scheme** & **parameter proliferation** (Armesto, Engemann, and Owyang, 2010)

Bias and inefficiency of the traditional models

- The FLAT-LS estimator is always relatively **less efficient** than the MIDAS-NLS estimator (Andreou, Ghysels and Kourtellos, 2010)
  - asymptotically **biased** and **inefficient** when high frequency regressors $\sim AR(1)$
- **Bias** of LS slope regression estimator when a **flat** weighting scheme is applied instead of a **non-flat** when the DGP is a MIDAS model (Andreou, 2016)
  - effective volatility forecast based on intra-daily squared returns
- MIDAS forecasts exhibit a relatively good balance concerning bias and estimation efficiency (Ghysels and Valkanov, 2012).

→ data-driven weights

MOTIVATION

Low-frequency process: **EU** GDP growth

High-frequency information: **EU Survey, Confidence Indicators (CIs)** or **Financial Indicators (FIs)**.

Estimating a MIDAS model instead of a standard Linear – LS model
→ *slope regression estimator*

- *with statistically significant* ***larger impact (≈bias)***
- *with statistically significant* ***forecasting gains***

→ *prominent role of the* ***Consumption Sentiment Indicator*** *as a predictor of the EU economic outlook*

Why “soft” indicators

Angelini, Mendez, Giannone, Reichlin, and Rünstler (2011)

- ***bridging*** *via factors from a large set of survey data and other “soft” information:* ***valuable*** *for nowcasting the EA GDP.*

Bánbura and Rünstler (2011)

- *survey & financial data:* ***important information*** *for the EA GDP forecasts when their* ***more-timely*** *publication is taken into consideration (****DFM*** *approach).*

Camacho and Perez-Quiros (2010)

- *business surveys gain importance compared to hard economic activity data in short-term forecasts of the EA GDP growth, subject to their* ***timeliness*** *(****DFM*** *approach).*

Why "soft" indicators

Girardi, Gayer, and Reuter (2015)

- *survey data*: ***timeliness is not their main/only 'quality'***
- *financial data*: ***important role*** *during the period of the Great Recession (2008–09).*
- *(**DFM blocking approach**)*

Andreou, Ghysels, and Kourtellos (2013)

- ***MIDAS*** *regression models using daily* ***financial*** *information* ***outperform*** *quarterly forecasts of* ***US*** *GDP growth based on quarterly macroeconomic factors.*

Monteforte and Moretti (2013)

- ***MIDAS*** *estimations based on high-frequency* ***financial*** *data reduce forecast errors of EA inflation compared to standard VAR models using lower frequency data.*

Ferrara and Marsilli (2013)

- *Relatively good predictive power of major* ***financial*** *variables (stock prices) versus the soft ESI in predicting the EA GDP growth through a* ***MIDAS*** *approach.*

The Common-frequency Regression Model

The basic single common-frequency regressor $\boldsymbol{ADL(p,q)}$ model for forecasting one quarter ahead the low-frequency macroeconomic variable, y_t^L, is given by:

$$y_{t+1}^L = \alpha + \sum_{i=1}^{p} \lambda_i L^i y_t^L + \sum_{j=1}^{q} \lambda_j L^j x_t^L + \varepsilon_{t+1}^L$$

p: lags of the low-frequency macroeconomic variable, y_t^L,

q: lags of the **aggregated** high-frequency soft variable, x_t^L,
(information criteria and serial correlation tests)

L^k: is the lag operator, $k = 1, \dots, K$.

$\uparrow p + q + 1$ estimated regression coefficients
$\downarrow$loss of information

Equal weights: $x_t^L = (x_{1,t}^H + x_{2,t}^H + x_{3,t}^H)/3 \rightarrow$ **not** optimal (memory decay)

The Mixed-frequency Regression Model

The single high-frequency regressor **ADL − MIDAS($\boldsymbol{p}, \boldsymbol{q}$)** model for h-steps ahead (low-frequency) forecasting with high-frequency data available up to x_t^H and low-frequency lags is (Andreou, Ghysels, and Kourtellos, 2013):

$$y_{t+h}^L = \alpha_h + \sum_{i=1}^{p} \lambda_{h,i} L^i y_t^L + b_h \sum_{k=1}^{K} w(k;\theta_h) L^{k/m} x_t^H + \varepsilon_{t+h}^L$$

$W\left(L^{1/m};\theta\right) = \sum_{k=1}^{K} w(k;\theta) L^{k/m}$ and $W(1;\theta) = \sum_{k=1}^{K} w(k;\theta) = 1$,

m: number of months per quarter

K: maximum number of high-frequency monthly lags

L^j and $L^{j/m}$ are lag operators for the low- and high-frequency data

- *ADL-MIDAS is a **direct forecasting tool** (time-series behaviour of the data)*
- ***Our analysis***: EMIDAS, BMIDAS, PMIDAS, and UMIDAS

European Union (EU) Empirical Results

Table: In-sample estimation results (1995Q1-2019Q4) of the **MIDAS** regression models when low-frequency variable is quarterly **EU GDP** and high-frequency predictors are monthly **Confidence Indicators (CIs)** vis-à-vis the corresponding **common-frequency Linear-LS models**.

	BMIDAS				EMIDAS			
	$\widehat{\boldsymbol{\beta}}_{GDP}$	$\widehat{\boldsymbol{\beta}}_{CI}$	BIC	LM	$\widehat{\boldsymbol{\beta}}_{GDP}$	$\widehat{\boldsymbol{\beta}}_{CI}$	BIC	LM
EUCONS	0.439***	**0.221*** **	**0.033**	**0.000**	0.519***	0.177***	**0.031**	**0.000**
EUESI	0.507***	0.139***	0.078	**0.022**	0.453***	**0.185*** **	0.056	**0.025**
EUINDU	**0.580*** **	0.075	0.131	**0.094**	0.477***	0.139***	0.129	0.341
	PMIDAS				**UMIDAS**			
EUCONS	0.429***	**0.221*** **	**-0.009**	**0.000**	0.519***	0.177***	**-0.062**	**0.000**
EUESI	0.499***	0.147***	0.029	**0.020**	0.453***	**0.185*** **	-0.038	**0.007**
EUINDU	**0.580*** **	0.075**	0.085	**0.094**	0.477***	0.139***	0.035	0.143
	LINEAR							
EUCONS	**0.540*** **	0.099***	0.119					
EUESI	0.406***	**0.158*** **	**0.038**					
EUINDU	0.392***	0.132***	0.057					

$\widehat{\boldsymbol{\beta}}$: *summations of lags based on the BIC criterion and serial correlation tests*

, **, **: *significance at 10%, 5%, 1% (two-sided p-values)*

LM Test:= $T(SSR_0^{LS} - SSR_1^M)/SSR_0^{LS} \xrightarrow{d} \chi^2(r)$

EU Out-of-sample Empirical Analysis: The forecasting performance of CIs

Training sample: 1995Q1-2007Q4

Evaluation sample: 2008Q1-2019Q4

Predictive models: $LINEAR$, $BMIDAS$, $EMIDAS$, $PMIDAS$, $UMIDAS$

Benchmark models: RW

Ratio of RMSFEs for each Confidence Indicator (CI) used in each model:

$$r_i = \frac{RMSFE_{predictive\ model,CI_i}}{RMSFE_{benchmark\ model}}$$

$r_i < 1 \rightarrow$ *forecasting models* ***beat*** *the benchmark models*

Table: Out-of-sample estimation results of quarterly **EU GDP** models: The Linear-LS regression model with common-frequency variables versus the alternative **MIDAS** models with higher-frequency monthly **sentiment** predictors.

Ratios of RMSFEs vis-à-vis the RW benchmark model					
	LINEAR	**BMIDAS**	**EMIDAS**	**PMIDAS**	**UMIDAS**
EUCONS	0.9048	**0.8108****	**0.8457***	**0.8075****	**0.8467***
EUESI	**0.8492**	0.8897	0.8792	0.8969	0.8792
EUINDU	0.8644	0.9164	0.9108	0.9164	0.9132
EUSERV	0.9246	0.9336	0.9906	0.9606	0.9767
EURETS	0.9478	0.9636	0.9602	1.0038	0.9602
EUBUILD	0.8938	0.8850	0.9332	0.8930	0.9332

*****: ∃ *significance based on the DM test*

Conclusions – EU Empirical Analysis with Confidence Indicators

- **MIDAS models reveal**:
  1. **Statistically significant larger estimated slope coefficients**, and
  2. **Forecasting gains** against $LINEAR - LS$ and traditional benchmark models.

- **MIDAS models reveal that EUCONS**:
  1. has among the **greatest impacts** on EU GDP growth,
  2. provides the **best-fitted model (BIC)**, and
  3. brings the **best out-of-sample predictor (RMSFE)**.

Barsky and Sims (2012): *surprise movements in consumption confidence are* ***prognostic*** *of long-lasting movements in macroeconomic variables*

Table: Out-of-sample estimation results of quarterly **EU GDP** models: The Linear-LS regression model with common-frequency variables versus the alternative **MIDAS** models with higher-frequency monthly **financial** and **sentiment predictors/combinations**.

Ratios of RMSFEs vis-à-vis the RW benchmark model					
	LINEAR	**BMIDAS**	**EMIDAS**	**PMIDAS**	**UMIDAS**
Stocks	**0.8485**	**0.8301**	**0.8312**	**0.8535**	**0.9013**
Euribors	0.9561	0.9483	0.9647	0.9657	0.9603
Commodities	0.9514	0.9571	0.9731	0.9607	0.9808
Sentiments	0.8492	**0.8108**	0.8457	**0.8075**	**0.8467**

Forecast combinations*: Simple mean, Simple median, Least-squares, Mean square error, MSE ranks, Smooth AIC weights, and SIC weights.*

EU CONCLUSIONS

- ***Omitted info***: problem regardless if the high frequency variable is a CI or a FI.

- MIDAS models in general provide:
  1. the highest gains in terms of MSFE vis-a-vis the benchmarks, and thus
  2. the highest gains in terms of MSFE vis-a-vis the Linear-LS model

*when the **financial predictors** are **Stocks** and **Euribor rates**, as well as when predictors are **Sentiment** indicators (in terms of best predictors/combinations).*

- MIDAS models reveal that the **Consumption CI**
  1. has among the **greatest impacts** on EU GDP growth,
  2. provides the **best-fitted model (BIC)**, and
  3. brings the **best out-of-sample predictor (RMSFE)**.

- *The **majority** of **MIDAS** models are in favor of the **Sentiment predictors**, whereas the **LINEAR-LS** model is in favor of the **Financial Stock predictors**.*

- **CONS > STOCK** **&** **MIDAS > LINEAR**

Individual European Country Results

Spain (ES) & United Kingdom (UK)

SPAIN (ES) CONCLUSIONS

- ***Omitted info***: problem regardless if the high frequency variable is a CI or a FI.
- MIDAS models in general provide:
  1. the highest gains in terms of MSFE vis-a-vis the benchmarks, and thus
  2. the highest gains in terms of MSFE vis-a-vis the Linear-LS model

*when the **financial predictors** are **Euribor rates** and **Commodity prices**, as well as when predictors are **Sentiment** indicators (in terms of best predictors/combinations)*

- MIDAS models reveal that the **Consumption CI**
  1. has among the **greatest impacts** on ES GDP growth,
  2. provides the **best-fitted model (BIC)**, and
  3. brings the **best out-of-sample predictor (RMSFE)**.

- ***All** the **MIDAS** models are in favor of the **Sentiment predictors**, whereas the **LINEAR-LS** model is in favor of the **Financial Stock predictors.***

  - **CONS > STOCK** & **MIDAS > LINEAR**

UNITED KINGDOM (UK) CONCLUSIONS

- ***Omitted info***: problem regardless if the high frequency variable is a CI or a FI.

- **MIDAS** models provide
  1. the highest gains in terms of MSFE vis-a-vis both benchmarks, and thus
  2. the highest gains in terms of MSFE vis-a-vis the linear LS model

*when **financial predictors** are either **Stock prices**, or **Euribor rates**, or **Commodity prices** and when **sentiment predictors** are **UKESI**, **UKINDU**, and **UKSERV**.*

- **UKBUILD** brings the **best out-of-sample predictor (RMSFE)** when the **LINEAR**, **BMIDAS**, and **PMIDAS** models are estimated, whereas **UKINDU** brings the best out-of-sample predictor when the **EMIDAS** and **UMIDAS** models are estimated.

- **Stocks** bring the best out-of-sample predictors when the **LINEAR**, **BMIDAS**, **PMIDAS**, and **UMIDAS** models are estimated, whereas **commodity prices** bring the best out-of-sample predictors when the **EMIDAS** model is estimated.

- ***All** models are in favor of the **Sentiment predictors**, except the **BMIDAS** model which is in favor of the **Financial Stock predictors.***
  - **BUILD > STOCK** & **MIDAS < LINEAR**

SUMMARY

1) In-sample & out-of-sample gains of the **MIDAS** models (EU evidence)
2) Vital role of **Consumption Sentiment Indicator** as a predictor of the EU economic outlook and other European countries closely related to it (e.g. Spain)
3) For economies **not** closely related to the EU (e.g. UK), the **Building Sentiment Indicator** seems to have a primary role for the UK economy and it is mainly exploited through **common-frequency estimations**.
4) The **Stock Price Indices** seem to have a strong leading ability compared to other financial predictors – evidence found for all three investigated economies (EU, ES, and UK).
   - Sentiments > Financial predictors

Thank you!