Daily growth-at-risk: financial or real drivers? The answer is not always the same

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Motivation I

- In recent years, policy has focused on tail risks and has motivated the development of new statistical tools to evaluate the likelihood of distress scenarios.
- Growth-at-risk approach, pioneered by Giglio et al. (2016) and Adrian et al. (2019).
  - Deteriorating financial conditions $\rightarrow$ Decline in future GDP growth.

Motivation I

- There is a large body of recent studies that analyze the predicting power of financial conditions on real economic activity in times of crisis.

  Giglio et al. (2016); Adrian et al. (2019); Arrigoni et al. (2020); Figueres and Jarociński (2020); Brownlees and Souza (2021).

- Basic idea: Financial markets and intermediaries act as amplifiers of shocks to the real economy.

  Brunnermeier and Sannikov (2016); Gertler and Gilchrist (2018).

Motivation I

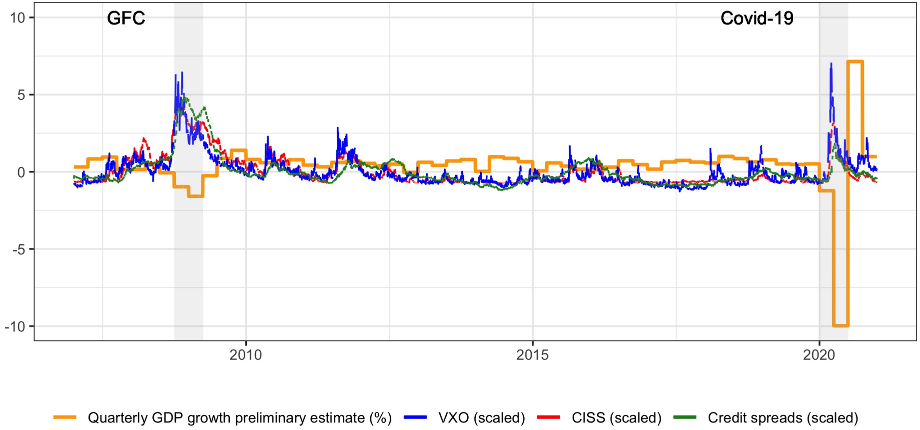

Figure 1: Quarterly GDP growth vs Daily financial indicators

Motivation I

- Are financial conditions the only source of GDP downside risks? What about real variables?

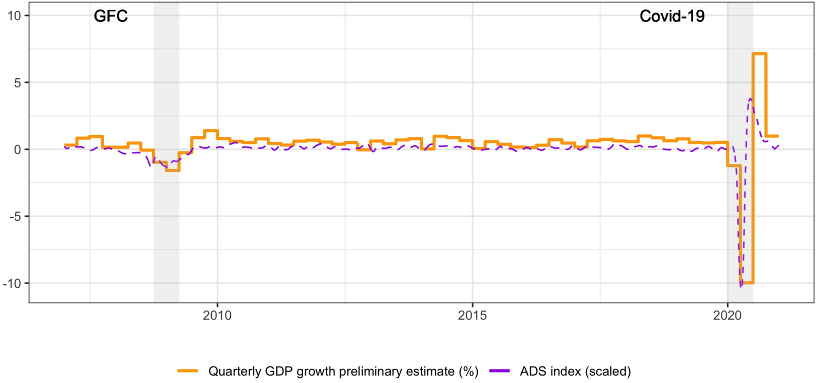

Figure 2: Quarterly GDP growth vs Aruoba-Diebold-Scotti Index

Motivation I

- Mixed evidence!

- After controlling for real variables, financial indicators have little to add to the mix (Reichlin et al., 2020; Plagborg-Møller et al., 2020).

- Real variables have little to add after financial variables have been incorporated into the forecasting equation (Carriero et al., 2022).

Contribution I

We recommend an eclectic approach be adopted:

Daily financial and real variables $\rightarrow$ Decline in current GDP growth.

Motivation II

- Financial conditions are usually taken as quarterly averages, but have higher frequency!

  Adams et al. (2021); Adrian et al. (2019); Figueres and Jarociński (2020); Brownlees and Souza (2021).

- Should we use instead high-frequency financial indicators (i.e, daily or weekly)?

  Ferrara et al. (2022); Carriero et al. (2022).

Motivation II

- Financial conditions are usually taken as quarterly averages, but have higher frequency!

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- Should we use instead high-frequency financial indicators (i.e, daily or weekly)?

  Ferrara et al. (2022); Carriero et al. (2022).

Contribution II

We use high-frequency daily financial and real indicators in pseudo real-time.

This paper

We propose a daily growth-at-risk (GaR) approach, based on high-frequency financial and real indicators, for monitoring downside risks in the US economy.

- High-frequency indicators (12)
- Seven different models (shrinkage and MIDAS).
- Forecast combination is applied to get a combined-GaR measure.
- Evaluation 1: traditional GaR vs our framework.
- Evaluation 2: Individual GaR vs combined-GaR.

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Data: Real Indicators

Real-time sample spans the period from Jan. 1, 1986 to Dec. 31, 2020.

1. Real Gross Domestic Product (GDP) collected in real-time.

2. ADS index weekly vintages collected in real-time from November 30, 2008.

- Note 1: Using weekly vintages reduce uncertainty at the sample endpoints (Amburgey and McCracken, 2022).
- Note 2: There is still uncertainty due to the estimation of the ADS index in a previous step (Maldonado and Ruiz, 2021).

Data: Financial Indicators

1. Interest rate spread (ISPREAD).
2. Effective Federal Funds Rate (EEFR).
3. Credit spread (CSPREAD).
4. Term spread (TERM).
5. Spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill (TED).
6. Excess return on the market (RET).
7. Returns on the portfolio of small minus big stocks (SMB).
8. Returns on the portfolio of high minus low book-to-market ratio stocks (HML).
9. Returns on a winner minus loser momentum spread portfolio (MOM).
10. CBOE SP 100 Volatility Index (VXO).
11. Composite Indicator of Systemic Stress (CISS).

Methodology: Nowcasting framework

- We extend Growth at Risk framework (Adrian et al., 2019) to account daily flow of information up to T.

$$\underbrace{Q_\tau(y_T)}_{\text{GDP growth}} = \beta_0(\tau) + \underbrace{\beta_1(\tau)y_{T-1}}_{\text{lagged GDP growth}} + \underbrace{X'_{T-h_d}\delta(\tau)}_{\text{Daily indicator}}$$

- In general, we want to produce:

$$GaR_T(10\%) = Q_{0.10}(y_T | y_{T-1}, X_{T-h_d})$$

- where $Q_{0.10}(.)$ comes from a mixed frequency model.

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Methodology: Nowcasting framework

- Let X_{t-h_d} be a p-dimension vector of 1 year daily lags of the high-frequency indicator.

$$X_{t-h_d} = [x_t^0, x_{t-1/60}^1, x_{t-2/60}^2, x_{t-3/60}^4, \dots, x_{t-239/60}^{239}]'$$

- with with $x_{t-h_d}^j$ and $h_d = (0, 1/d, 2/d, \dots, (p-1)/d)$.
- Notice that each $x_{t-h_d}^j$ is a quarterly time series.
- Still... We have a parameter proliferation problem (240 parameters)!

Methodology: Nowcasting framework

- In this setting, recall that the objective function to get the parameters is the minimization of the tick loss (TL) function.

$$TL_\tau = \frac{1}{T}\sum_{t}^{T}[\rho_\tau(y_t - \widehat{Q_\tau}(y_t))]$$

where $\rho_\tau = (1-\tau)\mathbb{1}_{e_t<0}|e_t| + \tau\mathbb{1}_{e_t>0}|e_t|$.

Models for $Q_{0.10}(.)$

1. Mixed data sampling quantile model (MIDAS-Q). go
2. Bayesian MIDAS (BMIDAS-Q), similar to Ferrara et al. (2021). go
3. LASSO quantile (Belloni and Chernozhukov, 2011). go
4. Elastic Net quantile (Zou and Hastie, 2005). go
5. Two step LASSO quantile (Lima and Godeiro, 2020).
6. Two step Elastic Net quantile (Lima and Godeiro, 2020). go
7. Adaptive sparse group LASSO (ASGL-Q), Mendez-Civieta et al. (2021). go

Forecast combination

- We rely on the discounted mean squared forecast error combinations approach (Stock and Watson, 2004; Andreou et al., 2013; Ferrara et al., 2020).

$$
\mathrm{w}_{i,t-h_d} = \frac{\lambda_{i,t-h_d}^{-\kappa}}{\sum_i^N \lambda_{i,t-h_d}^{-\kappa}},
$$

$$
\lambda_{i,t-h_d} = \sum_{s=T_o}^{T_f} \delta^{T_f - s}(y_s - GaR_{i,s}(10\%))(\tau - \mathbb{1}_{y_s < GaR_{i,s}(10\%)}),
$$

- with discount factor $\delta = 0.9$ and $\kappa = 1$.

- $s = T_o$ is the point at which the first prediction is computed, and $s = T_f$ is the point at which the most recent prediction can be evaluated.

Forecast combination

We compute the combined GaR recursively for each model (except for the ASGL-Q) as follows:

$$GaR^*_T = \Sigma_i w_{i,T-h_d} * Q_{0.10}(y_T, X^D_{i,T-h_d})$$

It is important to stress that the combined $GaR(10\%)$ does not include the CISS, as it is the benchmark financial composite indicator.

Pseudo algorithm for estimating combined GaR (except ASGL)

— For each model out of 6 models do:

—— For each high-frequency indicator out of 12 do:

——— For each day starting from January 1, 2007, do:

———— Step 1: Estimate $\hat{Q}_{0.10}(y_T|y_{T-1}, X^D_{i,T-h_d})$ and produce nowcast.

———— Step 2: Calculate combination weights $Q^T_{0.10}(y_T|y_{T-1}, X^D_{i,T-h_d})$.

—— Step 3: Compute individual-GaR.

— Step 4: Use optimal weights to compute combined-GaR.

Pseudo algorithm for estimating combined GaR with ASGL

——— For each day starting from January 1, 2007, do:

——— Step 1: Calculate group LASSO weights based on regression on a subset of principal components (Mendez-Civieta et al., 2021).

——— Step 2: Estimate combined-GaR directly via $\hat{Q}_{0.10}(y_T | y_{T-1}, X^{ASGL}_{T-h_d})$ and produce nowcast.

Forecast evaluation

1. Relative average TL (primary criteria) (see Gneiting and Raftery, 2007) with Diebold-Mariano test.

   Ha: The indicated forecast is more accurate than the benchmark forecast.

2. Unconditional coverage test: Is the coverage forecast adequate?

   Ho: The observed violation rate is statistically equal to the expected violation rate 10%.

3. Dynamic quantile test (Engle and Manganelli, 2004): Is the coverage forecast i.i.d.?

   Ho: The observed violation rate is i.i.d.

Empirical Results

- Best model: LASSO-Q. go
- Other models. go
- Evaluation 1: individual GaR (with CISS vs combined GaR (similiar to Adrian et al., 2019)). go
- Evaluation 2: combined GaR vs individual GaR (similiar to Figueres and Jarociński, 2020)). go

Conclusions

- Our framework can provide an early signal of GDP downturns in pseudo real-time that works well for both, the GFC and the Covid-19 episodes.
- VXO and CSPREAD are especially relevant across models in around the GFC, which highlights the prominent role of uncertainty in determining economic outcomes.
- Financial indicators alone were unable to forecast GDP low quantiles during Covid-19. Indeed, only by including the ADS index we managed to gauge both the sign and the magnitude of the downside GDP risk in this period.

Thank you! Comments welcome at igarron@ub.edu.

MIDAS-Q

Back

$$y_t = \beta_0(\tau) + \beta_1(\tau)y_{t-1} + \underbrace{\Sigma_{j=0}^{p-1} b(j;\theta(\tau))L^{\frac{j}{d}} x^j_{t-h_d}}_{\text{Almon Lag polynomial weighting}} + \epsilon_t(\tau)$$

- $j = (0, 1, 2, ..., p-1)$.
- $i = (0, 1, ..., c)$.
- We set $c = 3$ (third degree Almon lag).
- We use two end-point restrictions $r = 2$ (Mogliani and Simoni, 2021).
- Parameters for the high-frequency vector $c - r + 1 = 2$.

BMIDAS-Q

Back

This model estimates MIDAS-Q through Bayesian quantile regressions (Kozumi and Kobayashi, 2011).

- Standard uninformative priors on the coefficient vector $\beta \sim N(0, 9)$.
- For the autoregressive lag of GDP $\beta \sim N(0, 9)$.
- Scale and shape parameters of the inverse gamma function are set to 0.01.
- The Gibbs sampler is used to estimate the model parameters with 10,000 repetitions (for computation efficiency), after a burn-in period of 1,000 iterations (Yang et al., 2015).
- The choice of these parameters closely resembles the ones of (Ferrara et al., 2022), which is a natural benchmark model for our work.

EN-Q

Back

- As shown by Zou and Hastie (2005), we can reformulate the EN objective function as a LASSO problem:

$$min_{\phi^{++}} E[\rho_\tau(y_t^+ - X_t^+ \phi(\tau)) + \underbrace{\gamma(\tau)\Sigma_{j=0}^{p-1}|\phi_j(\tau)|]}_{LASSO}$$

- Where $\gamma(\tau)\frac{\lambda_{1,t}}{\sqrt{1+\lambda_{2,t}}}$ (LASSO penalization) is calculated as in Belloni and Chernozhukov (2011).
- $\lambda_{1,t}$ is set as LASSO-Q.
- $\lambda_{2,t}$ is minimizing the mean cross-validated errors of the model, with the EN mixing parameter set to $\alpha = 0.5$.

EN-Q selection of X_{t-hd}

Back

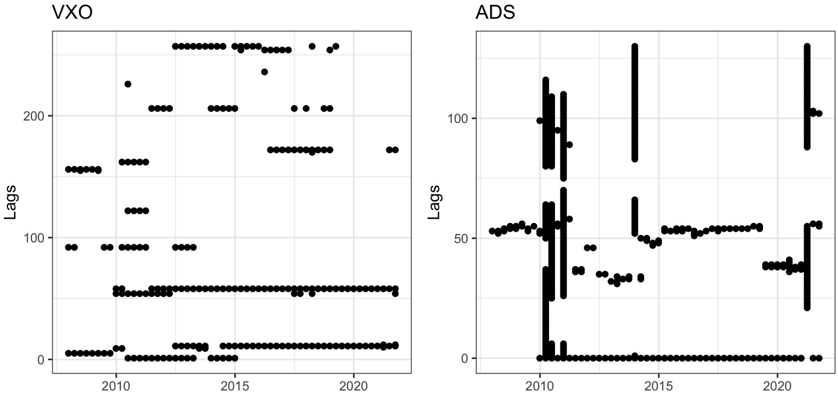

Figure 3: EN-Q selection by the end of quarter

Soft and hard threshold rules

Back

We consider the approach of soft and hard threshold methods applied to forecasting with many predictors (Lima et al., 2020; Bai and Ng, 2008).

1. Estimate principal components from the non-zero coefficients selected by LASSO-Q or EN-Q.
2. Select the optimal number of factors using the eigen ratio (Ahn and Horenstein, 2013).
3. keep the factors with associated p-values lower than 0.01 (or the statistically most significant ones)

LASSO (best model)

Back

- The objective function is:

$$min_{\phi} E[TL_{\tau}(\phi) + \underbrace{\alpha\lambda\frac{\sqrt{\tau(1-\tau)}}{T}\Sigma_{j=0}^{p-1}|\phi_j(\tau)|}_{LASSO}]$$

- The optimal level of λ_τ (LASSO penalization) is calculated as in Belloni and Chernozhukov (2011).
- Higher λ means higher penalization.

LASSO selection of X_{t-hd}

Back

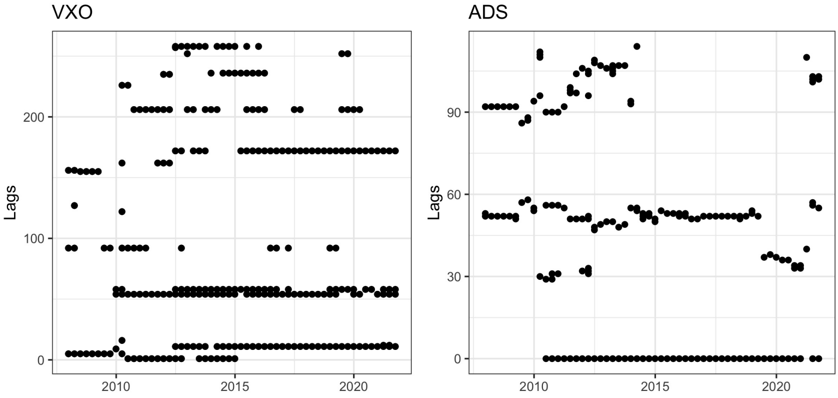

Figure 4: Lasso selection by the end of quarter

Adaptive sparse group LASSO (ASGL)-(Mendez-Civieta et al., 2021)

Back

- The objective function is:

$$min_\phi E[TL_\tau(\phi) + \underbrace{\alpha\lambda\Sigma_{j=0}^{k-1} w_j|\phi(\tau)_j|}_{LASSO*} + \underbrace{(1-\alpha)\lambda\Sigma_{l=0}^{m-1}\sqrt{p_l}v_l||\phi(\tau)^l||_2}_{\text{sparse group LASSO}}]$$

- $\tau = 0.10$.
- w_j is the weight for the j-th parameter.
- v_l is the weight for the l-th group of parameters (or high-frequency variable).
- $\alpha =$ LASSO vs sparse group LASSO.
- Cross validation is used for λ and α.
- $\lambda^* = 0.010$ and $\alpha^* = 0.25$.
- Computation of weights based on a subset of principal components (Mendez-Civieta et al., 2021).

Nowcasting Daily GaR (starting from January 1, 2007)

back

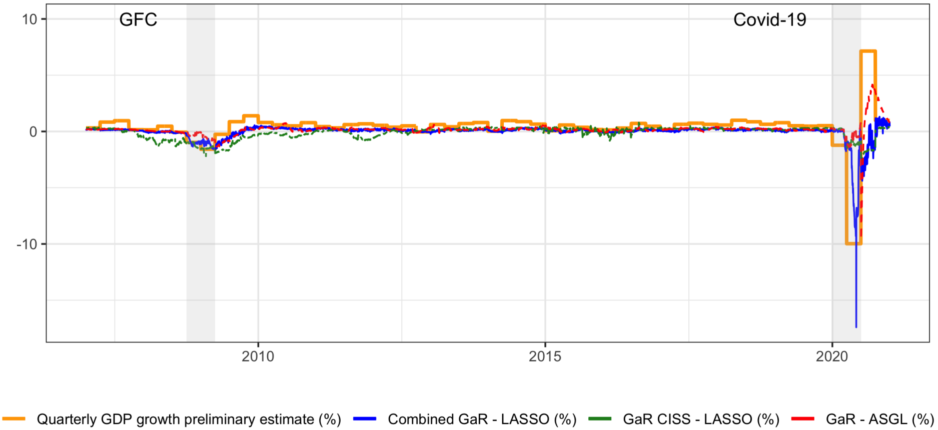

Figure 5: GaR results for LASSO-Q and AGLS-Q

Daily combination weights for LASSO

back

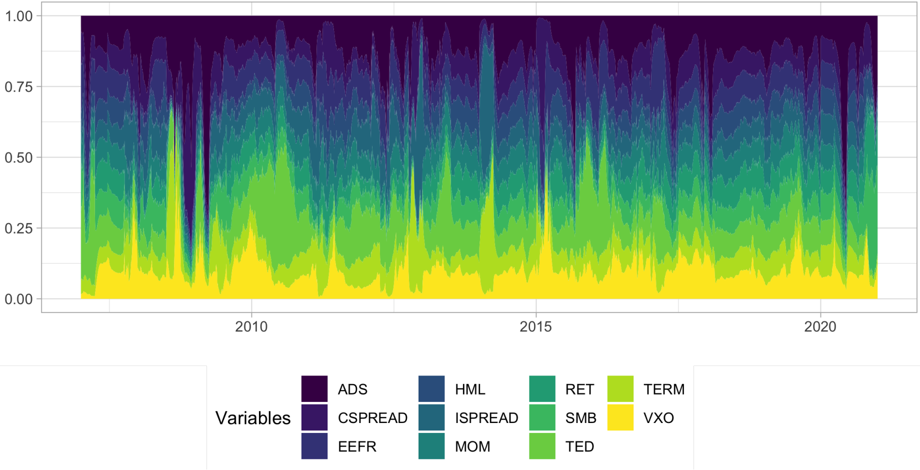

Figure 6: Daily weights for forecast combination.

Group weights for ASGL

back

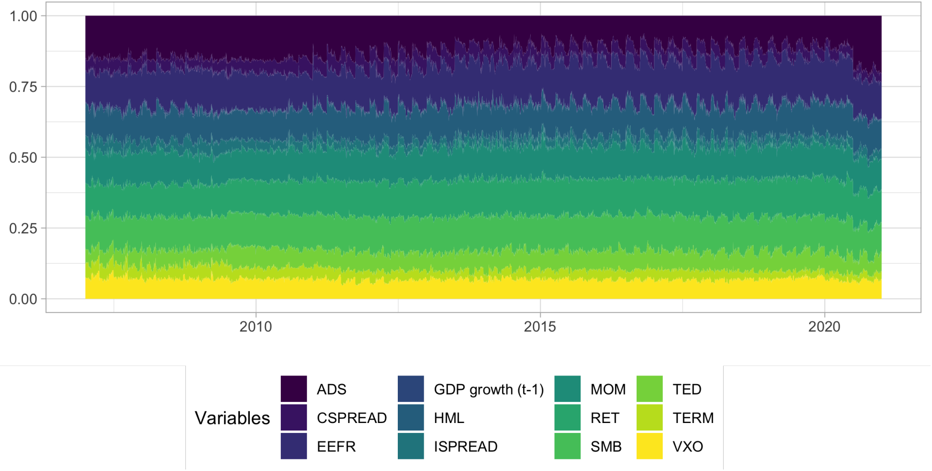

Figure 7: ASGL weights

Nowcasting Daily GaR (starting from January 1, 2007)

back

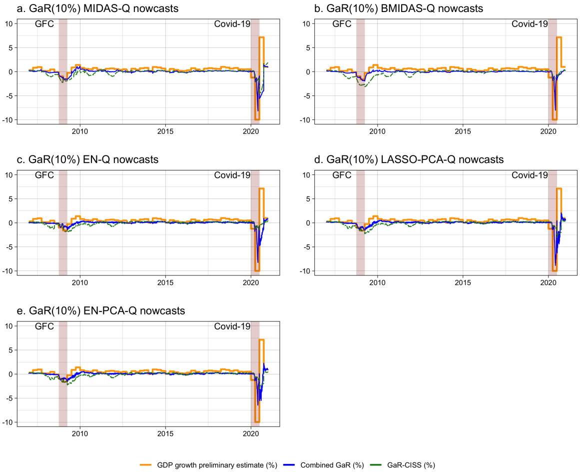

Figure 8: GaR results for other models

Evaluation 1: Traditional framework vs our framework I

	$h_d=0$		$h_d=10$		$h_d=20$		$h_d=40$		$h_d=60$	
	TL	DM	TL	DM	TL	DM	TL	DM	TL	DM
Panel A. Before COVID-19 (2007Q1 to 2019Q4)										
GaR^{MIDAS}	0.641	**0.001**	0.655	**0.001**	0.653	**0.000**	0.686	**0.001**	0.683	**0.001**
GaR^{BMIDAS}	0.606	**0.000**	0.616	**0.000**	0.631	**0.001**	0.643	**0.001**	0.654	**0.001**
GaR^{LASSO}	0.590	**0.001**	0.559	**0.000**	0.569	**0.000**	0.769	0.145	0.843	0.232
GaR^{EN}	0.956	0.415	0.978	0.461	0.932	0.366	0.853	0.273	0.858	0.277
GaR$^{LASSO-PCA}$	0.617	**0.001**	0.638	**0.002**	0.706	**0.010**	0.830	0.225	0.857	0.266
GaR^{EN-PCA}	0.617	**0.001**	0.691	**0.010**	0.741	**0.039**	0.809	0.176	0.844	0.251
GaR^{ASGL}	1.102	0.646	1.037	0.559	0.983	0.471	0.945	0.419	1.221	0.744
Panel B. Including COVID-19 (2007Q1 to 2020Q4)										
GaR^{MIDAS}	0.855	**0.027**	0.82	**0.005**	0.804	**0.022**	0.558	**0.094**	0.943	0.201
GaR^{BMIDAS}	0.878	**0.021**	0.849	**0.000**	0.839	**0.005**	0.558	**0.087**	0.932	0.141
GaR^{LASSO}	0.864	**0.002**	0.773	**0.006**	0.458	**0.096**	0.501	0.121	0.895	**0.092**
GaR^{EN}	0.953	0.243	0.969	0.330	0.822	0.153	0.563	0.139	0.917	0.173
GaR$^{LASSO-PCA}$	0.940	0.263	0.733	**0.041**	0.488	0.116	0.593	0.133	0.927	0.120
GaR^{EN-PCA}	0.911	0.102	0.850	**0.013**	0.841	**0.064**	0.691	0.116	0.903	0.123
GaR^{ASGL}	1.106	0.790	1.002	0.506	1.027	0.614	1.056	0.687	1.085	0.766

Evaluation 1: Traditional framework vs our framework II back

	$h_d = 0$		$h_d = 10$		$h_d = 20$		$h_d = 40$		$h_d = 60$	
	UC	DQ	UC	DQ	UC	DQ	UC	DQ	UC	DQ
Panel A. Before COVID-19 (2007Q1 to 2019Q4)										
GaR^{MIDAS}	0.001	**0.619**	0.019	**0.164**	0.019	**0.144**	0.019	**0.141**	0.001	**0.619**
GaR^{BMIDAS}	0.001	**0.619**	0.001	**0.619**	0.001	**0.619**	0.001	**0.619**	0.001	**0.619**
GaR^{LASSO}	0.019	**0.849**	**0.273**	0.014	**0.273**	0.018	0.095	**0.590**	0.019	**0.272**
GaR^{EN}	**0.273**	**0.180**	**0.273**	**0.218**	**0.926**	**0.126**	**0.273**	0.045	**0.273**	**0.107**
$\text{GaR}^{LASSO-PCA}$	0.095	**0.316**	0.095	**0.344**	**0.273**	**0.378**	0.095	**0.630**	0.095	0.011
GaR^{EN-PCA}	0.019	**0.842**	**0.565**	0.021	**0.273**	**0.386**	0.095	**0.603**	0.095	**0.631**
GaR^{ASGL}	**0.427**	0.013	**0.226**	0.071	**0.226**	0.044	**0.926**	**0.200**	**0.226**	**0.493**
Panel B. Including COVID-19 (2007Q1 to 2020Q4)										
GaR^{MIDAS}	**0.208**	0.001	**0.455**	0.045	**0.455**	0.085	**0.455**	0.024	**0.208**	0.003
GaR^{BMIDAS}	0.068	0.040	0.068	0.063	0.068	0.080	0.068	0.080	0.068	0.080
GaR^{LASSO}	0.068	**0.917**	**0.786**	0.000	**0.786**	0.021	**0.786**	0.042	**0.208**	**0.266**
GaR^{EN}	**0.786**	0.007	**0.786**	0.009	**0.547**	0.029	**0.786**	0.042	**0.786**	0.076
$\text{GaR}^{LASSO-PCA}$	**0.455**	**0.235**	**0.455**	0.009	**0.786**	0.036	**0.455**	**0.118**	**0.455**	0.008
GaR^{EN-PCA}	**0.208**	**0.468**	**0.547**	0.000	**0.860**	**0.202**	**0.455**	**0.130**	**0.455**	**0.677**
GaR^{ASGL}	**0.160**	0.015	0.031	0.000	0.031	0.000	**0.312**	**0.237**	**0.031**	**0.371**

Evaluation 2: Individual vs Combined-GaR for LASSO-Q I

	$h_d = 0$		$h_d = 10$		$h_d = 20$		$h_d = 40$		$h_d = 60$	
	TL	DM	TL	DM	TL	DM	TL	DM	TL	DM
	Panel B. Including COVID-19 (2007Q1 to 2020Q4)									
$GaR^{ISPREAD}$	1.445	**0.968**	1.555	**0.995**	1.530	**0.990**	1.837	**0.973**	1.346	**0.983**
GaR^{EEFR}	1.449	**0.982**	1.707	**0.992**	1.550	**0.987**	1.855	**0.963**	1.367	**0.979**
GaR^{RET}	1.408	**0.992**	1.556	**0.989**	1.503	**0.976**	1.776	**0.964**	1.208	**0.957**
GaR^{SMB}	1.271	**0.948**	1.510	**0.989**	1.301	**0.991**	1.667	**0.960**	1.302	**0.996**
GaR^{HML}	1.453	**0.995**	1.504	**0.983**	1.281	**0.913**	1.834	**0.942**	1.300	**0.975**
GaR^{MOM}	1.274	**0.981**	1.712	**0.971**	1.510	**0.969**	1.722	**0.934**	1.307	**0.988**
GaR^{VXO}	1.196	**0.908**	1.335	**0.995**	1.317	**0.994**	1.426	**0.893**	1.129	**0.950**
$GaR^{CSPREAD}$	1.336	**0.991**	1.351	**0.993**	1.280	**0.939**	1.501	**0.888**	1.133	**0.956**
GaR^{TERM}	1.42	**0.974**	1.502	**0.995**	1.432	**0.993**	1.789	**0.971**	1.334	**0.989**
GaR^{TED}	1.315	**0.960**	1.433	**0.994**	1.420	**0.985**	1.731	**0.950**	1.279	**0.980**
GaR^{ADS}	1.375	**0.923**	0.595	**0.174**	0.655	**0.159**	0.504	**0.152**	0.743	**0.260**

Evaluation 2: Individual vs Combined-GaR for LASSO-Q II back

	$h_d = 0$		$h_d = 10$		$h_d = 20$		$h_d = 40$		$h_d = 60$	
	UC	DQ	UC	DQ	UC	DQ	UC	DQ	UC	DQ
	Panel B. Including COVID-19 (2007Q1 to 2020Q4)									
$GaR^{ISPREAD}$	**0.312**	0.003	**0.312**	0.002	**0.312**	0.002	**0.547**	0.001	**0.547**	0.001
GaR^{EEFR}	**0.160**	0.007	0.031	0.000	0.074	0.001	0.031	0.002	0.012	0.000
GaR^{RET}	0.074	0.000	0.000	0.000	0.004	0.000	0.004	0.000	0.000	0.000
GaR^{SMB}	0.012	0.001	**0.160**	0.004	0.074	0.083	0.001	0.000	0.031	0.001
GaR^{HML}	0.004	0.000	0.012	0.000	0.031	0.001	0.001	0.000	0.004	0.002
GaR^{MOM}	**0.160**	**0.425**	**0.160**	0.018	0.004	0.001	0.004	0.000	0.074	0.000
GaR^{VXO}	0.031	**0.338**	0.004	**0.267**	0.001	0.011	0.004	0.042	0.004	**0.215**
$GaR^{CSPREAD}$	0.031	0.005	0.031	0.011	**0.160**	**0.204**	**0.160**	**0.427**	**0.547**	**0.921**
GaR^{TERM}	**0.547**	0.002	**0.547**	0.001	**0.547**	0.002	**0.312**	0.008	**0.860**	0.021
GaR^{TED}	0.031	0.003	0.012	0.000	0.012	0.000	0.004	0.000	0.004	0.001
GaR^{ADS}	0.074	**0.137**	0.004	0.003	0.031	0.001	0.074	**0.230**	0.031	0.018

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