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# Revisiting vulnerable growth in the Euro Area: Identifying the role of financial conditions in the distribution

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ABSTRACT

Growth-at-Risk modelling has been a cornerstone for research and policymaking recently as a way to model tail risk in the macroeconomy. However, the majority of the research has been almost exclusively been done on US data. The aim of this paper is to utilise a variable selection framework to identify which variables are key in capturing the different parts of the GDP distribution for the Euro Area. Importantly this paper uses a methodology that can handle variable selection task in small sample settings.



## 1. Introduction

The seminal publication of Adrian et al. (2019) has popularised the concept of tail risks in GDP growth, commonly referred to as Growth-at-Risk. The allure of the proposed method is that with quantile regression it allows for the modelling of tail risk conditional on variables, just like one would do with OLS (Koenker and Bassett, 1978). Apart from its simplicity, this approach fits nicely into prevailing policy frameworks such as Cecchetti (2008), Cecchetti and Suarez (2021), further highlighting its potential use in policy making.

There have been a great number of contributions to improve the modelling of Growth-at-Risk (see Carriero et al., 2020; Chen et al., 2021; Kohns and Szendrei, 2020 among others). Nevertheless, the majority of the research uses US data on account of the data requirement of quantile regression. Of the papers that do not use US data (such as Ferrara et al., 2022; Adrian et al., 2022; Galán, 2020 among others), Figueres and Jarociński (2020) is an important contribution, as it shows the potential to model tail risk using Euro Area data with the right financial conditions variable.

This paper combines the idea of Figueres and Jarociński (2020) and Kohns and Szendrei (2021) and identifies which financial conditions variables explain the different parts of the distribution. The main deviation from Figueres and Jarociński (2020) is that we allow for multiple financial conditions variables to be included in each quantile, if it improves overall fit. This was done because the different financial variables capture different aspects of financial risk and stress while the CISS is an aggregate. Note that Kohns and Szendrei (2021) takes a Bayesian approach to quantile specific sparsity, which we recast as a frequentist Adaptive LASSO (AdaLASSO). Furthermore, we impose noncrossing constraints to ensure monotonically increasing quantiles.

## 2. Data

The set of variables is as close as possible to that of Figueres and Jarociński (2020). Only a few additional variables are considered, namely retail spread for households, retail spread for nonfinancial corporations, year-on-year household loan growth, and year-on-year nonfinancial corporation loan growth. The variables used for estimation are shown in Table 1. The data are from 2003Q1 to 2019Q3, as such the Covid period does not influence our results.[1] Note, that GDP growth is included in this table but in an effort to keep as close to Adrian et al. (2019), its coefficient will not be penalised in this paper as opposed to Figueres and Jarociński (2020).

Of the variables in Table 1, the first are related to risks in the corporate bond market. Important, that all these indicators calculate the spread with respect to their domestic sovereign bonds of the same maturity, so as to not confound credit risk and term premiums. Note that unlike Figueres and Jarociński (2020), we also include the Bund base for the Bank Bond and NFC Bond spread for the measures of Gilchrist and Mojon (2018).

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[1] Inclusion of the COVID period does not change the conclusion. Results for the model run on 2003Q1 to 2022Q1 are included in the Appendix.

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**Table 1**
Variable set.

| Indicator | Description |
|---|---|
| GDP growth | Quarter-on-quarter GDP growth |
| High Yield bond spread | ICE BofA Euro High Yield Index |
| Bank Bond spread | Bank bond spread (EA and Bund base) from Gilchrist and Mojon (2018) |
| NFC bond spread | NFC Bond spread (EA and Bund base) from Gilchrist and Mojon (2018) |
| Retail lending spread | Lending rate to non-financial private sector minus 3 m Euribor |
| Retail lending spread (Household) | Cost of borrowing for housing loans minus 1y Euribor |
| Retail lending spread (NFC) | Cost of borrowing for non financial corporations minus 3 m Euribor |
| Loan Growth (Household) | Year-on-year growth of household loan stock |
| Loan growth (NFC) | Year-on-year growth of non financial corporation loan stock |
| TED spread | 3 m Euribor minus 3 m BuBill |
| Term spread | 10y Bund minus 3 m BuBill |
| Sovereign spread | Euro Area 10y sovereign yield minus 10y Bund yield |
| VSTOXX | 30-day implied volatility of EURO STOXX 50 |
| CISS | Composite Indicator of Systemic Stress (Hollo et al., 2012) |

Due to bank lending being more prevalent than bond financing in the euro area, we include several measures tracking lending in the euro area. The retail lending spread measures the difference between the interbank rate and the rate charged to the non-financial private sector. We also consider the lending spread to households and non financial corporations separately as potential financial indicators.[2]

The final set of spread measures is the TED spread, capturing credit risk on the interbank market; the Term spread, a measure of the yield curve; and the Sovereign spread, reflecting the riskiness of the Euro Area relative to the safest Euro government bond.

The implied volatility of the EURO STOXX 50 index is also considered as a potential variable. This measure is aimed to capture overall uncertainty of the stock market in the Euro Area. The last indicator considered is the Composite Indicator of Systemic Stress (CISS) of Hollo et al. (2012) which is a nonlinear aggregation method that captures episodes when multiple indicators are simultaneously high.[3]

## 3. Methodology

A natural way to extend Figueres and Jarociński (2020) is to create models that describe the best k-variable quantile models which do not cross. Given that the best model might have different number of variables depending on the quantile, one would need to run a plethora of different combinations of variables. Luckily selecting a subset of variables can be recast into a shrinkage problem (Hastie et al., 2009). In this paper we opt for the LASSO shrinkage as it is a continuous model selection technique discarding predictors from the model by shrinking their coefficients exactly to 0 (Tibshirani, 1996).

[2] Note that the sector specific spreads use a composite cost of borrowing as a measure rather than pure interest rates to make retail spreads more comparable (and thus easier to aggregate) across the Euro Area. Furthermore, since the cost of borrowing of the Household sector pertains to housing loans, the spread is based on the difference between the cost of borrowing and the 1 year Euribor.

[3] For country specific applications one can use the CLIFS of Duprey et al. (2017) instead of the CISS.

The method employed in this paper is very close to Jiang et al. (2014), with the adjustment that interquartile deviation is left un-shrunk. Instead non-crossing constraints are imposed following Bondell et al. (2010). Formally we estimate the following set of equations:

$$
\begin{aligned}
\hat{\beta}(\tau) = & \min_{\beta,\alpha} \sum_{q=1}^{Q}\sum_{i=1}^{n} \rho_{\tau_q}(y_i - \alpha_{\tau_q} - x_i^T\beta_{\tau_q}) \\
& s.t.\ \alpha_{\tau_{q-1}} + x^T\beta_{\tau_{q-1}} \le \alpha_{\tau_q} + x^T\beta_{\tau_q} \\
& \sum_{q=1}^{Q}\sum_{k=2}^{K} w_{k,\tau_q}|\beta_{k,\tau_q}| \le t^*
\end{aligned}
\tag{1}
$$

where $\rho_{\tau_q}$ is the tick-loss function of Koenker and Bassett (1978). The above set of equations estimates all $Q$ quantiles simultaneously, which are enforced to be monotonically increasing through the inclusion of the non-crossing constraints. Shrinkage of parameters starts from $k = 2$, so as to not shrink the parameter of GDP growth and the constant.

The set of equations describe an AdaLASSO shrinkage with weights $w_{k,\tau_q}$. Following Jiang et al. (2014), we will define the weights as $w_{k,\tau_q} = |\theta_{k,\tau_q}|^{-1}$, where $\theta$ are the estimated coefficients of a regular quantile regression using the full design matrix.

The second constraint in Eq. (1) is the AdaLASSO constraint, which allows the sum of the coefficients to be at most $t^*$. Most LASSO formulations represent the estimator in Lagrangian form, where the Lagrange multiplier, $\lambda$, regulates the maximum variation of the coefficients. Note, that there is a direct inverse relationship between the $t^*$ in Eq. (1) and $\lambda$ (Ahrens et al., 2022).

The selection of a "global" variation parameter, $t^*$, is in stark contrast to Kohns and Szendrei (2021), where the parameter dictating variable selection is quantile specific. The choice for a global parameter, is driven by the fact that less data is available. As such, as more data becomes available it will be interesting to redo this exercise with quantile specific $t^*$.

To obtain the optimal $t^*$ parameter a grid search will be employed. For each candidate hyperparameter, Eq. (1) will be run. The model with the lowest information criteria (AIC or BIC) is chosen as the optimal model.[4] It is important to note that the coefficients of these estimates are biased downwards, so a second estimation is done where the parameters not chosen by the LASSO are constrained to 0. The coefficient of this second model are the final estimates.

When doing regularised regression it is common to standardise the data, so as to make the scales equal for each variable. Since we are following Bondell et al. (2010), we make our variables be on the domain of [0,1]. As such no further data transformation is necessary since the non-crossing implementation already standardises our data.

In summary this paper tackles the constraints on data availability on two fronts: (1) it imposes non-crossing constraints to help the estimation through enforcing the monotonicity assumption; and (2) it has only a global variation parameter rather than a quantile specific one.

## 4. Results

### 4.1. LASSO results

The results are displayed in Fig. 1, for one quarter ahead estimates, and Fig. 2, for one year ahead estimates. These figures plot the LASSO coefficients as we allow for more variation in the

[4] For further information please see the Appendix.

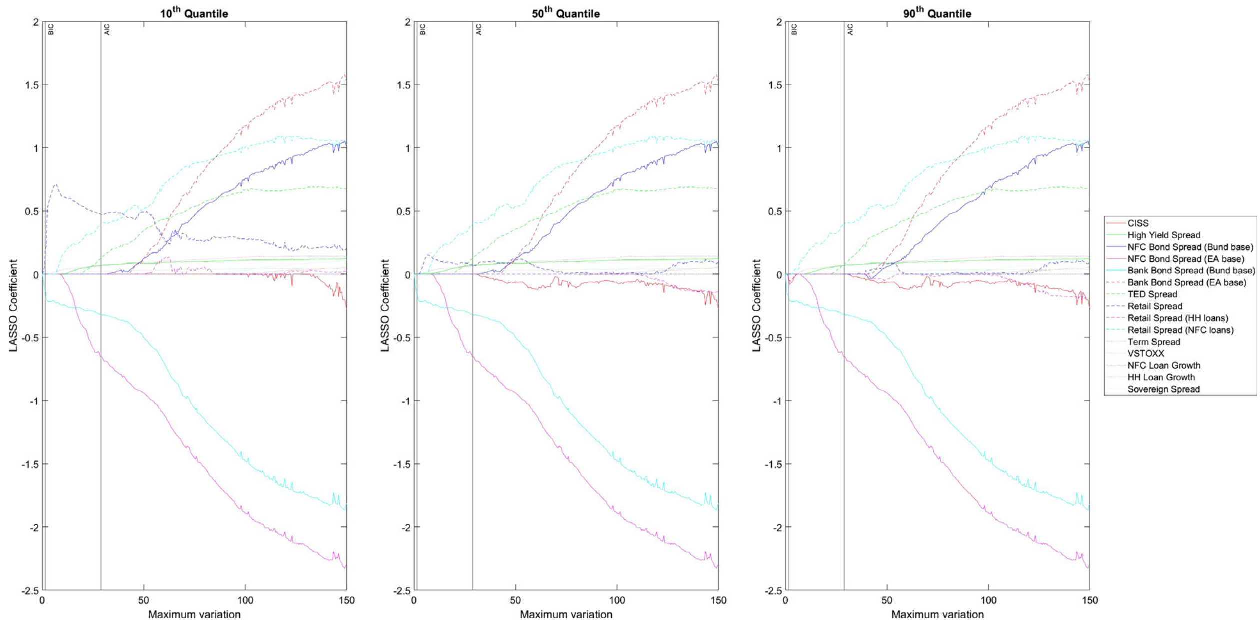


**Fig. 1.** Variable selection results when h=1.

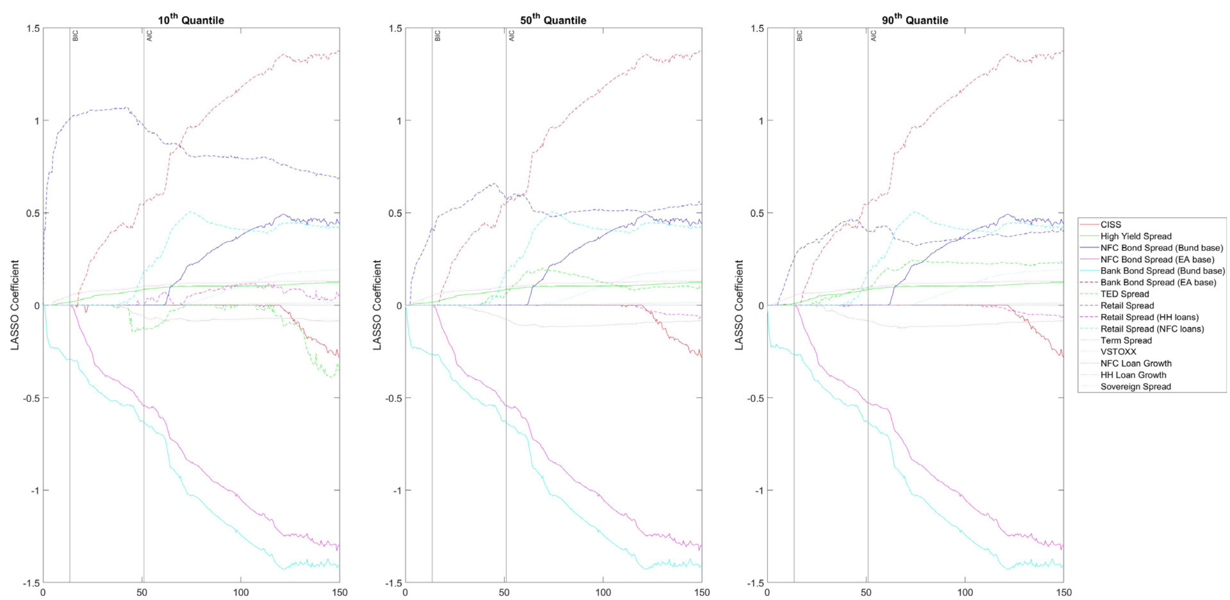


**Fig. 2.** Variable selection results when h=4.

estimated model. The optimal $t^*$ selected by the AIC and BIC is also shown in these figures as a vertical line.

When allowing for multiple variables to be included, the CISS is not chosen as a variable. This is true regardless of the forecast horizon and information criteria used. This is in stark contrast to the finding of Figueres and Jarociński (2020), who find that the CISS yields the best model fit at the one year ahead forecast horizon, while we find that a collection of other variables are preferred over the inclusion of the CISS.

We find that at the longer forecast horizon, more variables are selected in the optimal model when using the BIC as a selection criteria. This is in line with Kohns and Szendrei (2021) for US data, who find that with longer forecast horizons, more variables are needed to capture Growth-at-Risk estimates.

We can see that the first variable being selected at the lowest quantile, is the retail spread for both forecast horizons. However, this is not the true across the distribution: Bank bond spread (Bund base) is chosen first at the median and upper quantile for both forecast horizons. This is congruent with Kohns and Szendrei (2021), who find that different variables are important for different parts of the distribution.

### 4.2. Optimal BIC model

Table 2 shows the coefficients of the optimal model. Since the goal of the paper is to identify the most parsimonious linear approximation of Growth-at-Risk, we will use the BIC when choosing the optimal model. For the sake of brevity, unselected variables are not shown in this table.

A couple of points emerge from this table. First, just like the case for the first relevant variable, in the optimal model, the variables that explain the different parts of the distribution are

**Table 2**
Coefficients of the BIC selected model at h=1 and h=4.

| | h=1 | | | h=4 | | |
|---|---|---|---|---|---|---|
| | $\tau_q = 0.1$ | $\tau_q = 0.5$ | $\tau_q = 0.9$ | $\tau_q = 0.1$ | $\tau_q = 0.5$ | $\tau_q = 0.9$ |
| Constant | −1.383 | 0.933 | 1.493 | −2.240 | −0.748 | 0.018 |
| GDP growth | 0.429 | 0.273 | 0.228 | 0.002 | 0.002 | 0.002 |
| High Yield Spread | | | | 0.023 | 0.022 | 0.015 |
| NFC Bond Spread (EA base) | | | −0.107 | | | |
| Bank Bond Spread (Bund base) | −0.234 | −0.234 | −0.260 | −0.316 | −0.285 | −0.285 |
| Bank Bond Spread (EA base) | | | −0.003 | | | |
| Retail Spread | 0.640 | | | 1.087 | 0.618 | 0.426 |
| HH Loan Growth | | | | 0.082 | 0.082 | 0.081 |

not the same for the shorter forecast horizon. In particular we can see that retail spread is chosen for the lower quantile only, while Bank Bond Spread (EA base) and NFC Bond Spread (EA base) are only selected for the upper quantile. Bank Bond Spread (Bund base) is the only variable chosen for all quantiles (apart from GDP growth which is forced to be included). Importantly, the sign of the selected variables does not "flip" as we move up the quantiles which means the sparsity at the median is not on account of the variable being shrunk because its coefficient is near 0 as it changes sign.

Second, not all variables portray quantile variation at all quantiles. For example the coefficient on lagged GDP at the longer forecast horizon is identical across the quantiles. This is indicative of constant $\beta$ profiles across some quantiles. Interestingly, this behaviour is more prevalent at one year ahead forecast horizon.

Looking at the optimal models lowest quantile, we can see that the one-quarter ahead model includes Retail Spread. Together with the Bank Bond Spread (Bund base) these two variables offer a better in-sample fit than the CISS. At the longer forecast horizon these variables are included as well with the same sign but two additional variables are needed for the best fit, namely the High Yield Spread and Household Loan Growth. Interestingly, most of the variables selected are in relation to the banking sector. The retail spread, and Household Loan Growth are both directly related to banking activities, while the Bank Bond Spread is a measure of the markets perception of bank's health. This highlights the importance of the Bank sector for the Euro Area.

### 4.3. Comparison to CISS-only model

To verify the performance of the optimal model versus a CISS (and GDP) only model, we evaluate model performance using in sample fit at selected quantiles. Since the degrees of freedom differs between the optimal model and the CISS only model, we will use $BIC_q$ to compare in sample fit of selected quantiles. Note, that this BIC is not the same as was used to select the optimal $t^*$: the $BIC_q$ only looks at the fit of the particular quantile, while the BIC used for the selection of the optimal model looked at the overall fit of all quantiles jointly. The results are shown in Table 3.

Looking at the results reveals that the Optimal model performs better at all parts of the distribution, leading to the lowest $BIC_q$. This is true for both forecast horizons considered. Importantly, these results are not driven by the inclusion of the non-crossing constraints only.[5]

**Table 3**
In sample fit for the models at h=1 and h=4.

| | $\tau_q = 0.1$ | $\tau_q = 0.5$ | $\tau_q = 0.9$ |
|---|---|---|---|
| *h=1* | | | |
| Optimal model | 1.749 | 2.436 | 1.375 |
| Non-Cross Reg. (CISS only) | 1.822 | 2.504 | 1.524 |
| Quantile Reg. (CISS only) | 1.818 | 2.504 | 1.524 |
| *h=4* | | | |
| Optimal model | 1.341 | 2.109 | 0.936 |
| Non-Cross Reg. (CISS only) | 1.777 | 2.393 | 1.386 |
| Quantile Reg. (CISS only) | 1.739 | 2.391 | 1.379 |

**Table 4**
Out of sample fit for the models at h=1 and h=4.

| | Left tail | Centre | Right tail |
|---|---|---|---|
| *h=1* | | | |
| Optimal model | 0.030 | 0.019 | 0.045 |
| Non-Cross Reg. (CISS only) | 0.032 | 0.019 | 0.044 |
| Quantile Reg. (CISS only) | 0.033 | 0.019 | 0.045 |
| *h=4* | | | |
| Optimal model | 0.023 | 0.014 | 0.035 |
| Non-Cross Reg. (CISS only) | 0.021 | 0.013 | 0.033 |
| Quantile Reg. (CISS only) | 0.020 | 0.013 | 0.034 |

## 5. Conclusion

This paper highlights the values of looking at vulnerable growth from the perspective of quantile specific sparsity. When doing so we can get Growth-at-Risk estimates that rival the model with only the CISS. Importantly, this paper tackles the problems of insufficient data by imposing non-constraint constraints and a global shrinkage parameter.

To summarise, we echo the findings of Kohns and Szendrei (2021) and find evidence for quantile varying sparsity. In contrast to Figueres and Jarociński (2020) we find that a combination of other variables is selected over only the CISS at the forecast horizons considered. Finally, the majority of the variables selected are in relation to the banking sector, highlighting how the Euro Area largely relies on bank financing. As such the authors suggest that when modelling Euro Area Growth-at-Risk, one should opt for a selection of bank variables, rather than solely relying on the CISS. The results are verified by the $BIC_q$, which shows that the optimal model consistently outperforms the CISS (and GDP) only variant.

## Data availability

Data will be made available on request.


## Acknowledgements

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[5] For out of sample results please see the Appendix.

**Table 5**
Coefficients of the BIC selected model at h=1 and h=4 for the longer sample.

| | h=1 | | | h=4 | | |
|---|---|---|---|---|---|---|
| | $\tau_q = 0.1$ | $\tau_q = 0.5$ | $\tau_q = 0.9$ | $\tau_q = 0.1$ | $\tau_q = 0.5$ | $\tau_q = 0.9$ |
| Constant | −0.828 | 1.439 | 2.039 | −1.608 | 1.145 | 1.390 |
| GDP | −0.015 | −0.015 | −0.048 | 0.062 | 0.062 | 0.061 |
| High Yield Spread | | | | 0.014 | 0.014 | 0.007 |
| NFC Bond Spread (Bund base) | −0.462 | −0.462 | −0.462 | | | |
| Bank Bond Spread (Bund base) | −0.070 | | −0.051 | −0.291 | −0.287 | −0.287 |
| Retail Spread | | | | 0.864 | | |
| Retail Spread (HH loans) | 0.877 | | | | | |
| NFC Loan Growth | | | | | | 0.017 |

**Table 6**
In sample fit for the models at h=1 and h=4 for the longer sample.

| | $\tau_q = 0.1$ | $\tau_q = 0.5$ | $\tau_q = 0.9$ |
|---|---|---|---|
| *h=1* | | | |
| Optimal model | 3.174 | 3.400 | 2.996 |
| Non-Cross Reg. (CISS only) | 3.247 | 3.432 | 2.985 |
| Quantile Reg. (CISS only) | 3.241 | 3.432 | 2.977 |
| *h=4* | | | |
| Optimal model | 2.330 | 2.878 | 2.227 |
| Non-Cross Reg. (CISS only) | 2.569 | 2.944 | 2.291 |
| Quantile Reg. (CISS only) | 2.566 | 2.941 | 2.280 |

## Appendix

### *A.1. $t^*$ selection*

There are several ways to select the optimal $t^*$. Leave Future Out Cross-Validation is a popular choice in time series settings. The key idea of cross validation is to break down the sample into a training sample (where coefficients are estimated) and a testing sample (where model fits are evaluated). This way one is able to achieve a model that does not overfit, but it requires a sufficient amount of data. On account of the small sample size we opt to use methods that look at in-sample fit only but penalise for model complexity:

$$IC(t^*) = \sum_{q=1}^{Q} log\Big[\sum_{i=1}^{n} \rho_{\tau_q}(y_i - \alpha_{\tau_q}(t^*) - x_i^T \beta_{\tau_q}(t^*))\Big] + P(t^*) \tag{2}$$

where $P(t^*)$ is some penalty function penalising model complexity. In the notation above, the coefficients (and penalty) are a function of $t^*$, which is the amount of maximum variation allowed in Eq. (1). The penalty function for the AIC and BIC are:

$$\begin{aligned} P_{AIC}(t^*) &= \frac{1}{n} \sum_{q=1}^{Q} \sum_{j=1}^{K} \mathbb{I}(\beta_{\tau_q,j}(t^*) > 0) \\ P_{BIC}(t^*) &= \frac{log(n)}{2n} \sum_{q=1}^{Q} \sum_{j=1}^{K} \mathbb{I}(\beta_{\tau_q,j}(t^*) > 0) \end{aligned} \tag{3}$$

When substituting Eqs. (3) into Eq. (2) it is clear that there is a trade-off between model fit and the number of parameters included in the sample. This way we can infer the model fitting performance of models with different number of explanatory variables as long as the dependent variable is unchanged. Note that the above AIC and BIC are the information criteria used for model selection. When evaluating model fit of a specific quantile in-sample in Table 3, we do not sum over the quantiles.

### *A.2. Out of sample results*

To gauge whether there is over-fitting a small out of sample forecast exercise is also run. The optimal model and the CISS only model are run with a sample size of 50, which is expanded 1 period at a time. The betas are then used to fit the next out of sample period. These fits are then compared using the quantile weighted CRPS of Gneiting and Ranjan (2011). The weights for the left tail, right tail, and centre will be presented. Note that due to the small sample size (for $h = 1$ we have a total of 16 out of sample fits) the results should be used as general guidance only. The results are shown in Table 4.

The out of sample results are in stark contrast to the in sample fits. First we see bigger difference between the two models at the left tail only. This highlights how financial conditions variables have a larger influence on the lower tail of the GDP growth distribution. This is in accordance with the main findings of Adrian et al. (2019).

Second, we see that for the shorter forecast horizon the Adaptive LASSO selected model has gains, while for the longer forecast horizons, the CISS only model seems better. Looking at the included variables in Table 1 and the optimal model for $h = 4$ in Table 2 we can conclude that the latter is on account of only including few variables that track financial stress developing in the longer run, namely the loan growth variables. Potentially, with more variables that track slow moving financial conditions, a better long term forecasting model can be developed.

### *A.3. Inclusion of COVID period*

Running the variable selection on a longer sample of 2003Q1 to 2022Q1 does not drastically change the model results. The BIC selected optimal model on the longer sample is shown in Table 5. While the model does not select the exact same variables, the optimal model on the longer horizon selects very similar variables. As such the key takeaways are not impacted: (1) not all variables portray quantile variation, (2) a selection of bank sector variables offers better fit than the CISS only. Furthermore, on the longer sample there is evidence of quantile specific sparsity for both forecast horizons.

In sample fits of this optimal model and the CISS only models are shown in Table 6. Note, how the optimal model remains the best choice, except for the upper quantile when $h = 1$. As such, one can conclude that the method selected optimal model remains the best choice for describing growth-at-risk in the Euro Area.

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