Growth Fragility and Systemic Risk under Model Uncertainty

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Abstract

The link between systemic risk and economic growth is hard to study because the relationship is believed to be nonlinear and systemic risk is unobservable. The myriad of measures proposed in the literature add model uncertainty as an additional difficulty. I use a Bayesian quantile regression to study the relevance of 33 systemic risk indicators to explain lower quantiles of output growth. Model uncertainty is tackled with sparse and dense modelling techniques that perform both model selection and shrinkage. I find that systemic risk indicators add value to quantile forecasts of GDP growth, in-sample and out-of-sample. However, less than halve of the indicators considered are selected to explain the different quantiles of economic growth.

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1 Introduction

The global financial crisis that started in 2007 has brought systemic risk to the forefront of the research agenda of academics and policymakers. On the empirical side, the literature has focused on measuring systemic risk in an effort to provide indicators of financial imbalances in the economy, hoping that these might serve as early warnings of forthcoming recessions. This has led to the proposal of a myriad of indicators, aimed at capturing different dimensions of systemic risk. Billio et al. (2012) and Bisias et al. (2012) survey over 30 such indicators, many more have been proposed since. The staggering amount of systemic risk indicators proposed in the literature owes to the fact that the definition of systemic risk is rather diffuse. As a result, different measures capture different dimensions of the concept. Nevertheless, a synthesis and working definition is provided by Peydro et al. (2015), that introduces systemic risk as *the risk of threats to financial stability that impair the functioning of a large part of the financial system with significant adverse effects on the broader economy*[1]. A key element that distinguishes a systemic event from otherwise systemically unimportant shocks, that are constantly hitting the financial system without resulting in a crisis, is its macroeconomic relevance. Whether an episode is classified as systemic therefore depends on its impact on welfare and real activity [2]. Overall, systemic risk indicators are expected to signal downside risks to real activity and reflect the likelihood of a recession.

This paper investigates the relevance of 33 popular systemic risk indicators in predicting different quantiles of the predictive distribution of GDP growth by deploying a Bayesian quantile regression model. Sparse-modelling techniques are used to address model uncertainty concerns, related to the large number of predictors, allowing for both model selection and shrinkage. We focus on selecting a small set of explanatory variables with the highest predictive power, out of a much larger set of regressors which characterize systemic risk. In virtue of the *a-priori* uncertainty regarding the level of sparsity suitable to characterize the link between systemic risk and real activity, which we aim to represent, we propose a simple probabilistic framework in which it is easy to compare different regularization techniques. Reassuringly, key results are common across shrinkage methods. We find that the information contained in systemic risk indicators helps predict various quantiles of the predictive distribution of GDP growth in-sample and out-of-sample. Nevertheless, few measures out of the 33 systemic risk indicators we considered are selected as relevant predictors. Moreover, the information in systemic risk indicators doesn't seem to contain recession-specific predictive power - the number of indicators selected as relevant in predicting the lower tails of the distribution of GDP growth is not significantly different from those selected as predictors of central moments.

Our contribution relates to a rapidly growing body of literature that examines macroeconomic tail risks related to financial variables. Adrian et al. (2019), Adrian et al. (2018), Nicolò and Lucchetta (2017) and Giglio et al. (2016) suggest that the

[1]This definition is broadly consistent with that proposed by the IMF, FSB, ECB and BIS (see International Monetary Fund (2009); Hartmann et al. (2009); Caruana (2010)).

[2]Laeven and Valencia (2013) compile a comprehensive dataset of cross-country banking crisis from 1970 to 2011 and identify 147 systemically important banking crisis that result in an average output loss of 23 per cent.

relationship between real activity and financial conditions is non-linear and asymmetric, emphasizing that poor financial conditions pose risks to economic growth, shifting the lower tail of its predictive distribution outwards.

New research is building on these insights. Adrian et al. (2018), defines the concept of Growth-at-Risk (GaR) - the value of GDP growth evaluated at a given low percentile τ of the predictive growth distribution. Figueres and Jarociński (2020) find a similar link between financal conditions and macroeconomic tail risk in the euro-area. Brownlees and Souza (2021) extensively backtest (out-of-sample) the GaR for 24 OECD countries using GARCH models in addition to quantile regressions which are the prevalent tool in the literature to evaluate macroeconomic tail risk. Carriero et al. (2020a) examine the suitability and performance of Bayesian VARs with stochastic volatility in capturing macroeconomic tail risks, following Chavleishvili and Manganelli (2019) which introduce quantile VARs. Both conclude that quantile regression methods are not superior to other valid alternatives to study tail risk.

A common thread in the literature is the need to deal with the high dimensionality of the set of potential predictors which characterize financial conditions in the economy. Giglio et al. (2016) and Adrian et al. (2019) and other papers which build on their findings, use dense-modelling techniques to address the issue. The synthetic index of financial conditions used by Adrian et al. (2019) is a Principal Component of 105 individual financial variables, relevant to the US economy.[3] Principal Component Analysis has proven effective in reducing model dimensionality and is widely used in the literature[4]. It is based on the principle that all potential predictors might be relevant and thus shrinks the information content in all variables into a few factors that explain the maximum amount of variation in the pool of regressors. In this context, the main disadvantages of this framework has to do with interpretability and information loss. Although shrinking the information content of a large pool of systemic risk indicators into a few factors is effective in dealing with model uncertainty and avoiding the curse of dimensionality, it is unable to inform which systemic risk indicators signal risks to output growth, since that information is lost in the shrinkage process. This opens the question of whether a model representation featuring disaggregated financial variables can advance our understanding of the dynamics of macroeconomic downside risk.

We examine the relevance of 33 of the most popular systemic risk indicators proposed in the literature in light of sparse-modelling methods which provide information about the individual relevance of each indicator in predicting downside risk to GDP growth. We specify a *Stochastic Search Variable Selection (SSVS)* prior following the original proposal of Mitchell and Beauchamp (1988) and Korobilis (2017) in a quantile regression framework. Such an approach is justified by statistical reasons - to avoid overfitting and unnecessary parameter proliferation (see Stock and Watson (2006) and Koop and Korobilis (2011)) but also on economic grounds - Giglio et al. (2016) suggests that a small subset of systemic risk indicators are relevant in describing the interaction between systemic risk and real activity. The

[3] The authors use the Chicago Fed National Financial Conditions Index (NFCI)

[4] See for example Bernanke et al. (2005); Koop (2013); Boivin et al. (2018); Bok et al. (2018) and Stock and Watson (2016a) for a review.

pattern of sparsity emerging from the data allows us to answer the questions: i) Do systemic risk indicators help in forecasting macroeconomic risk ? ii) Which systemic risk indicators contain recession-relevant information ?

Our approach is similar to that of Reichlin et al. (2020) who examine the relevance of disaggregated macroeconomic and financial data in predicting macroeconomic tail risk. Similarly, Plagborg-Møller et al. (2020) evaluate the information content of 102 macroeconomic and financial variables to predict growth-at-risk for 13 advanced economies by using (*inter alia*) Bayesian quantile regression methods with a *horseshoe* prior of Carvalho et al. (2010) which implies an a-priori belief in approximate sparsity. One aspect that distinguishes our exercise from the extant literature is that we access the relevance of systemic risk indicators in particular to predict downside risk to real activity in light of different shrinkage techniques extending the analysis of Giglio et al. (2016). In addition, from an econometric point of view, our probabilistic specification of the quantile regression model allows the econometrician to evaluate whether the results are an artifact of strong prior beliefs favouring sparsity (see Giannone et al. (2017) for a discussion). Our starting point is a standard Bayesian quantile regression proposed by Kozumi and Kobayashi (2011). We describe the precise blocks in the Markov Chain Monte Carlo (MCMC) algorithm that need to be changed in order to alternate between SSVS, the Bayesian Lasso and the Ridge estimators.

Few papers contrast the results from sparse *versus* dense modelling approaches to access the relevance of individual financial variables in predicting macroeconomic risk. An early paper by Manzan (2015) contrasts quantile forecasts obtained via quantile regression where principal components and Lasso are used as alternative data reduction techniques. Monache et al. (2020) employ the *shrink-then-sparsify* approach of Hahn and Carvalho (2015) to deal with the large number of predictors that feed into the National Financial Conditions Index - used in this literature to proxy of financial conditions. Unlike other common shrinkage methods (such as the Ridge and Lasso) their hybrid approach allows for a fully adaptive shrinkage procedure at a coefficient-level. Cook and Doh (2019) find evidence that a dense model using Principal Components as predictors of macroeconomic tail risk may be misspecified. The authors argue that such misspecification stems from the *"common slope"* assumption implicit when using Principal Components, which ignores the possibility of different predictors featuring in different quantiles of the predictive distribution of macroeconomic outcomes. The granularity of our approach allows different predictors to be selected for inclusion in different quantiles of the predictive distribution of GDP growth. Our strategy to address the *a-priori* uncertainty regarding the degree of shrinkage employed is to contrast the results of the SSVS with those of the Bayesian Lasso and the Ridge estimators. Although some remarkable differences can be noted, reassuringly key results can be observed across regularization techniques.

The exercise offers new insights on the relevance of systemic risk indicators for macroeconomic forecasting. The literature that preceded the Great Recession has documented the unpredictability of GDP growth during the Great Moderation (see eg. D'Agostino et al. (2006); Rossi and Sekhposyan (2010)) and the fragile and unreliable predictive content of financial indicators (Stock and Watson (2003) Forni et al. (2003) and Hatzius et al. (2010)). The idea that financial and economic conditions exhibit a non-linear correlation has inspired new research on this subject. Giglio et al. (2016) finds that few systemic risk measures possess significant predictive content for downside quantiles of macroeconomic shocks. Reichlin et al. (2020) conclude that overall, financial variables provide limited leading information about GDP risk. The authors find that the NFCI contains limited leading information on forthcoming recessions. Whereas, non-financial leverage provides a leading signal of downside risk. The out-of-sample, real time forecasting exercise conducted by Plagborg-Møller et al. (2020) also suggests that financial variables contribute little to quantile forecasts of real activity, beyond the information contained in other real economic indicators. Nevertheless, the authors stress that the VXO, the spread between AAA corporate bonds and 10-year Treasuries; and various measures of credit quantity may be relevant. Reichlin et al. (2020) evaluates the out-of-sample performance of key financial variables and finds little evidence that these add value to forecasting macroeconomic tail-risk.

Other authors find encouraging results about the value of financial variables to forecast macroeconomic tail risk. Using mixed-frequency models, estimated at a weekly frequency, Carriero et al. (2020b) find that stock prices, term-spreads, credit spreads and the NFCI improve tail-nowcasts of economic activity. Monache et al. (2020) highlight that indicators of excess-leverage, household credit and credit spreads are drivers of downside risk and that financial conditions significantly contribute to the accuracy of macroeconomic tail risk forecasts.

Two sets of results emerge from our exercise and contribute to this discussion. First, overall we find that taken together, systemic risk indicators add value to quantile forecasts of GDP growth. We verify that this result holds across sparse/dense modelling assumptions, in-sample and out-of-sample. Second, these results seem to be driven by few systemic risk indicators which are selected for inclusion in the model, across quantiles. The term spread, a series of credit spreads, the Debt-Service-Ratio, the size concentration in the financial sector, the cyclically adjusted price-to-earnings ratio and the VXO are indicators consistently chosen as relevant predictors of lower quantiles of GDP growth. The number of predictors featured in the model decreases quite significantly for the forecast horizons of four and eight quarters ahead. The information content of credit spreads in particular seems to be only relevant in the short-term.

The remainder of the paper proceeds as follows. Section 2 presents the data and section 3 explains the econometric framework, estimation technique, variable selection and shrinkage procedure. Section 4 discusses the main results and findings. Section 5 concludes.

2 Data

An overwhelming quantity of systemic risk measures have been proposed in the literature. We restrict our attention to those for which data is available, relying on the surveys of Bisias et al. (2012) and Giglio et al. (2016). In addition to the indicators considered by the aforementioned authors, we study a number of related indicators that were not considered in their articles but are relevant to our analysis.

Table 1: Measures of systemic risk considered and respective sample dates.

#	Systemic Risk indicator	Sample	Reference
1	absorption	1947-2011	Kritzman et al. (2011)
2	Delta Absortion	1947-2011	Kritzman et al. (2011)
3	AIM	1947-2011	Amihud (2002)
4	CatFin	1947-2011	Allen et al. (2012)
5	GZ spread	1973-2011	Gilchrist and Zakrajsek (2012)
6	Baa/Aaa Bond yield	1947-2011	Giglio et al. (2016)
7	TED spread	1984-2011	Stock and Watson (2003)
8	Term Spread	1947-2011	Stock and Watson (2003)
9	Baa/10-yr T-rate spread	1962-2011	Stock and Watson (2003)
10	Mortg-GS10 Spread	1971-2011	Stock and Watson (2016b)
11	Comm. paper-3mT-Bill spread	1959-2011	Stock and Watson (2016b)
12	Excess Bond Premium	1973-2011	Gilchrist and Zakrajsek (2012)
13	Intl. Spillover	1963-2011	Diebold and Yilmaz (2011)
14	CoVaR	1947-2011	Adrian and Brunnermeier (2016)
15	Delta CoVaR	1947-2011	Adrian and Brunnermeier (2016)
16	Book lvg.	1969-2011	Giglio et al. (2016)
17	Mkt. Lvg.	1969-2011	Giglio et al. (2016)
18	DCI	1947-2011	Billio et al. (2012)
19	MES	1947-2011	Acharya et al. (2017)
20	MES-BE	1947-2011	Brownlees and Engle (2012)
21	Volatility	1947-2011	Giglio et al. (2016)
22	Size conc.	1947-2011	Giglio et al. (2016)
23	Turbulence	1947-2011	Kritzman and Li (2010)
24	PQR	1947-2011	Giglio et al. (2016)
25	Average DD.	2008-2011	Saldias (2013)
26	portfolio DD.	2008-2011	Saldias (2013)
27	MRI CITI Index	1997-2011	Adrian et al. (2010)
28	CAPE	1947-2011	Shiller (2005)
29	VXO	1962-2011	Bloom (2009)
30	Sent. Index	1965-2011	Baker and Wurgler (2006)
31	Credit-to-gdp gap	1962-2011	Aldasoro et al. (2018)
32	Debt Service Ratio	1999-2011	Aldasoro et al. (2018)
33	Loan Supply	1990-2011	Lown and Morgan (2006)

The table above summarizes all measures that we consider as potential predictors of downturns in economic activity, the sample period for which they are available and respective references. A more detailed explanation of the data, transformations and sources used is provided in the Appendix. In what follows we explain the econometric approach we adopt to investigate the link between the 33 measures described and different quantiles of economic growth.

3 Bayesian Quantile Regression

We wish to explain the τth quantile of output growth between period t and t+h, denoted by y_{t+h}, by regressing this time series on a set of explanatory variables that include systemic risk indicators and also relevant own lags of real activity, organized in a matrix x_t of dimensions $T \times K$, where T is the time dimension and K the number of regressors. Analytically, the τth quantile of y_{t+h} is given by its inverse probability distribution function denoted

$$\mathbb{Q}_\tau(y_{t+h}) = inf\{y : P(y_{t+h} \leq y) \geq \tau\}. \tag{1}$$

The quantile function can be expressed as the solution of the minimization problem

$$\mathbb{Q}_\tau(y_{t+h}) = min_q \mathbb{E}(\rho_\tau(y_{t+h} - q)), \tag{2}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ is refered to in the literature as the quantile loss function. In the seminal paper by Koenker and Bassett (1978) the conditional quantiles of y_{t+h} are expressed as functions of the set of observables in a form similar to the following equation

$$y_{t+h} = x_t' \beta_\tau + \varepsilon_t. \tag{3}$$

The main advantage of quantile regression is that the coefficients β_τ are allowed to vary across quantiles τ, capturing non-linear dynamics between real activity and systemic risk as prescribed by theory. It also gives a richer picture of the uncertainty surrounding point forecasts and how such uncertainty depends on measures of systemic stress. We are particularly interested in lower quantiles of real activity that depict economic downturns.

Estimation is trivial in a classical framework and proceeds by solving the optimization routine specified in (2). However, it is advantageous to formalize the model in a bayesian setting to address our concerns over model uncertainty and to deal with the large number of predictors that have been found, in different contexts, to result in in-sample overfitting due to the proliferation of parameters (see Stock and Watson (2006) and Koop and Korobilis (2011)). The application of Bayesian methods to equation (3) is however, not straighforward *a priori* because the innovations ε_t are not normally distributed. Indeed, Yu and Moyeed (2001) show that the solution to (2) is equivalent to the maximization of a likelihood function under the asymmetric Laplace error distribution. Because the asymetric Laplace distribution can be represented as a scale mixture of normals (see Kotz et al. (2001)), the quantile regression (3) may be respecified such that Gibbs Sampling methods can be applied. Following Kozumi and Kobayashi (2011) we rewrite the error distribution as

$$\varepsilon_t = \theta z_t + \phi \sqrt{z_t} u_t, \tag{4}$$

where $z_t \sim Exp(1)$ and u_t is a standard normal distribution. $\theta = (1 - 2\tau)/\tau(1 - \tau)$ and $\phi = 2/\tau(1 - \tau)$, for a given quantile $\tau \in [0, 1]$. By plugging expression 4 into equation 3 we obtain a new quantile regression that can be estimated with Bayesian methods

$$y_{t+h} = x_t' \beta_\tau + \theta z_t + \phi \sqrt{z_t} u_t. \tag{5}$$

In the next section we show that the choice of specific priors allow for shrinkage and model selection in regression (5).

3.1 Model Selection and Shrinkage

The first step in Bayesian inference is the specification of prior distributions for all relevant parameters. Priors allow the researcher to include additional relevant information in the analysis. In this exercise, we use priors as a device to address our concerns over both model uncertainty and in ensuring a parsimonious representation of the relationship between systemic risk and real activity.

Model uncertainty arises from the large number of systemic risk indicators that aim at approximating different aspects of systemic risk. Understanding which particular indicator merits inclusion in the regression to explain growth fragility is unclear *a priori* but important for two main reasons. First, it is essential to understand from which part of the financial system risks are originating. Secondly, from a statistical viewpoint, it is necessary to assess the predictive content of each systemic risk measure to understand its suitability as an early warning indicator of a recession.

Describing the relation between systemic risk and real activity in a parsimonious way is motivated by statistical reasons - to avoid overfitting and unnecessary parameter proliferation (see Stock and Watson (2006) and Koop and Korobilis (2011)); but it is also justified on economic grounds - Giglio et al. (2016) suggests that a small subset of systemic risk indicators are relevant in describing the interaction between systemic risk and output. We specify the following priors

$$\beta_\tau|\gamma_\tau, \delta_\tau \sim N(0, \gamma_\tau\delta_\tau^2), \tag{6}$$

$$\delta_\tau^{-2} \sim Gamma(a_1, a_2). \tag{7}$$

This multi-level prior specification where β_τ is conditionally normal, allows for automatic shrinkage and model selection through the parameter γ_τ, that shrink β_τ to zero for any coefficient delivering poor fit. This setting offers several possibilities to impose sparsity in the model. In what follows we review three such alternatives that are nested in this framework.

3.1.1 Stochastic Search Variable Selection

Similar to the *Stochastic Search Variable Selection (SSVS)* prior originally proposed by Mitchell and Beauchamp (1988), in our setting each coefficient in β_τ takes non-zero values with probability π_0. We refer to these hyperparameters as the probabilities of inclusion. Our approach follows that of George and McCulloch (1993) and Korobilis (2013) in the sense that our prior for the coefficients is conditionally Gaussian albeit in the context of quantile regression closer to the work of Korobilis (2017). Formally, this prior forms a hierarchical structure that extends (6) and (7) by adding the following hyperpriors to that setting

$$\gamma_\tau|\pi_0 \sim Bernoulli(\pi_0), \tag{8}$$

$$\pi_0 \sim Beta(b_0, b_1). \tag{9}$$

Because γ_τ is a vector of binomial variables , only the systemic risk indicators with the highest predictive power will be included in the regression. Moreover, the probability of inclusion of each indicator defined by π_0 is also random, thus controlling the degree of shrinkage automatically. Hence, if $\gamma_{i,\tau} = 0$, the parameter

$\beta_{i,\tau}$ is shrank to zero. Whereas, if $\gamma_{i,\tau} = 1$, the prior for $\beta_{i,\tau}$ will follow a normal distribution centered in zero. Since γ_τ is estimated from the data, within a standard Gibbs Sampler, examining the posterior of γ_τ may inform which variables are most relevant in explaining each quantile of real activity.

3.1.2 Bayesian Lasso

An alternative method capable of selecting relevant variables in a linear regression framework has been proposed by Tibshirani (1996) and is widely known as Least Absolute Shrinkage and Selection Operator (Lasso). The Lasso is part of a wider class of penalized regression models that work by adding a penalty term to the objective function from which the coefficient estimates derive, and has been shown to be effective in quantile regression (see Wu and Liu (2009); Li and Zhu (2008))[5]. The Lasso owes its name to the form of penalty imposed. It works by adding an L1-norm regularizer on the prediction weights standing for the absolute value of magnitude of the coefficients.

The Lasso regression estimates can be given a Bayesian interpretation as it has been shown that, for specific choices of priors, the mean or mode of the posterior distribution of the parameters are equivalent to penalized regression results. Park and Casella (2008) show that the Lasso estimate can be interpreted as a Bayesian posterior mode estimate when the parameters have independent Laplace priors [6]. Moreover, the authors show that the Laplace distribution can be written as a scale mixture of normals with an exponential mixing density. Hence, the Bayesian Lasso can be obtained by specifying a hierarchical structure that extends (6) and (7) by adding the following hyperpriors to that setting

$$\gamma_\tau | \lambda \sim \mathcal{E}(2/\lambda^2), \tag{10}$$
$$\lambda^2 \sim Gamma(c_0, c_1). \tag{11}$$

Where $\mathcal{E}(.)$ denotes a exponential distribution with mean $2/\lambda^2$. The Normal-Inverse Gamma prior layer in (6)-(7) remains valid, except that in (6), the prior variance should be changed to $\Omega = diag(\gamma_\tau)$ [7].

Contrary to its frequentist sibling, the Bayesian Lasso in our framework allows for the automatic choice of the degree of shrinkage λ. In our application the degree of shrinkage is driven by data since λ is random and has its own posterior density. The main idea underlying these prior choices is similar. We wish to shrink nuisance parameters and sparsify the model such that a clearer pattern of the most important systemic risk indicators might emerge.

[5]It works by solving the following optimization problem, $\beta^L = \text{argmin}_\beta\, \rho_\tau \varepsilon'\varepsilon + \lambda \|\beta\|_1$, where $\|\beta\|_1 = \sum_{j=1}^{p} \beta_j$ and λ controls the amount of regularization, that ensures shrinkage towards zero and prevents overfitting (see Kapetanios et al. (2018) for a review of penalised regression techniques in a linear regression setting and Li et al. (2010) that discusses variable selection and shrinkage in a Bayesian quantile regression setting.)

[6]Although it is worth noting that, unlike its frequentist sibling, the Bayesian Lasso delivers posterior distributions which concentrate poorly in sparse models (see Castillo et al. (2015))

[7]see Kozumi and Kobayashi (2011) section 3.2.

3.1.3 Bayesian Ridge

The Ridge estimator is another special case of the penalized regression where an L2-norm regularizer is added to the objective function of the estimation problem [8]. The Ridge regression was first introduced by Hoerl and Kennard (1970) and the main idea resembles the previous methods discussed. Similar to the Lasso, the Ridge regression also has a Bayesian analogue, that can be obtained simply by specifying Normal-Inverse Gamma priors for the regression parameters such as in (6) and (7). Hence, if no other hyperpriors are added to the primary specification defined by (6) and (7), or if we set $\pi_0 = 1$ in the SSVS setting, the Ridge regression emerges by default (see Kapetanios et al. (2018) and Giannone et al. (2017)).

3.2 Estimation

The parameters in (5) can be estimated with a Gibbs Sampler since the respective likelihood function is conditionally Gaussian written as

$$f(\mathbf{y}|\beta_\tau, \mathbf{z}) \propto \prod_{i=1}^{T} z_t^{-1/2} \times exp\Big\{ -\frac{1}{2}\sum_{i=1}^{T} \frac{(y_t - x_t'\beta_\tau - \theta z_t)^2}{\phi^2 z_t} \Big\}, \tag{12}$$

with $\mathbf{y} = (y_1, ..., y_T)'$ and $\mathbf{z} = (z_1, ..., z_T)'$. A full characterization of a Gibbs Sampler pass-through in our exercise is provided in Appendix B. The algorithm builds on the procedure suggested by Korobilis (2017) using different priors in order to implement the three variable selection techniques discussed. In Appendix D we assess the convergence of the Gibbs Sampler employed.

4 Discussion of the Results

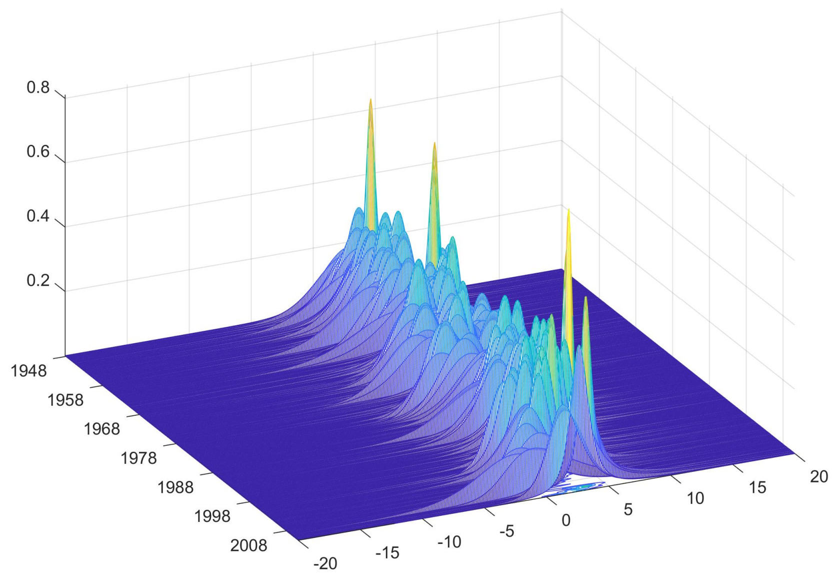
In this section we discuss the results that emerge from the estimation of the quantile regression which yields a predictive distribution of GDP growth, conditional on the set of systemic risk indicators considered. We focus on two main questions. First, which systemic risk indicators explain in-sample the variation of different quantiles of real activity - in particular lower quantiles, that are associated with recessions. Second, we assess the out-of-sample performance of the quantile regression estimated with the SSVS prior, which is our baseline specification.

An interesting exercise that quantile regressions allow for is to examine the full predictive distribution of GDP growth. Unlike normal linear models, quantile regressions yield complex predictive distributions that need not be symmetric. We are particularly interested in the shape of its lower tail, since it reflects the likelihood of economic downturns. Figure 1 shows the predictive distribution of GDP growth, one-year ahead, conditional on systemic risk, which we call growth surface. It results from the estimation of our baseline quantile regression specification (5) for the grid of quantiles $\tau = \{0.05, 0.25, 0.5, 0.75, 0.95\}$ for the full sample period. For each element in τ, we obtain a quantile forecast which is the median of our MCMC

[8] The Ridge estimator is found by solving $\beta^R = \text{argmin}_\beta\, \rho_\tau \varepsilon'\varepsilon + \lambda \, \|\beta\|_2$ with $\|\beta\|_1 = \sum_{j=1}^{p} \beta_j^2$.

draws. We then follow Adrian et al. (2019) and fit a skew-t density to our quantile forecasts.

Figure 1: Growth Surface. Predictive density of GDP growth, conditional on Systemic Risk.



Notes: The growth surface results from the estimation of the Quantile Regression with the baseline SSVS prior for each quantile in τ and interpolated with a skew-t distribution.

The figure suggests the predictive distribution of GDP growth is left-skewed, a finding that is not new and consistent with the results discussed by Adrian et al. (2019).

A discussion of two relevant challenges related to the use of quantile regression-based tools for quantifying tail risks in macroeconomics is in order. First, in the quantile literature, it is found that estimating extreme quantiles with small samples of data may result in coefficient bias and unreliable inference (see Tetsuya Kaji et al. (2017)) and extremal quantile methods have been developed to conduct inference in such cases. In our exercise, we keep with the literature assessing tail risks in macroeconomics and refrain from conducting inference for quantiles τ above 0.95 and below 0.05 and approach our results for more extreme quantiles with caution. Second, quantile regressions often lead to what is known in the literature as quantile crossing (cf. Bassett and Koenker (1982)). This problem consist in a lack of monotonicity of the estimated conditional quantile functions, which leads to spurious inference on the predictive distribution, fitted across quantiles. While such issue is common and has been documented in a similar setting by Carriero et al. (2020a), we do not encounter such a problem in our exercise.[9]

A closer look at the coefficient estimates can inform about which systemic risk indicators contain relevant information in predicting GDP growth. We examine

[9] Carriero et al. (2020a) find that, to some extent, Bayesian shrinkage tends to mitigate this problem.

the indicators picked as relevant predictors of the full spectrum of the GDP growth distribution by the different shrinkage algorithms. We start by discussing estimation results for the quantile regression with the SSVS prior which is our benchmark choice for implementing variable selection. It enforces sparsity in the model because the posterior distribution of the coefficients inherits the priors' shape, with probability mass in zero.

Table 2: Systemic Risk indicators selected as relevant in explaining different quantiles of the predictive distribution of GDP growth at different horizons.

#	Systemic risk indicator	predictors at horizon h = 1					predictors at horizon h = 4					predictors at horizon h = 8				
		$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.75$	$\tau = 0.95$	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.75$	$\tau = 0.95$	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.75$	$\tau = 0.95$
1	absorption					•		•					•			
2	Delta Absorption			•												
3	AIM		•	•	•											
4	CatFin															
5	GZ spread															
6	Baa/Aaa Bond yield													•	•	
7	TED spread															
8	Term Spread		•	•	•	•		•	•	•	•	•	•	•	•	•
9	Baa/10-yr T-rate spread	•			•	•				•	•			•	•	•
10	Mortg-GS10 Spread	•	•													
11	Comm. paper-3mT-Bill spread	•	•					•								
12	Excess Bond Premium															
13	Intl. Spillover		•	•												
14	CoVaR	•	•		•	•			•		•					•
15	Delta CoVaR	•	•			•					•					•
16	Book lvg.				•	•					•					
17	Mkt. Lvg.					•										
18	DCI															
19	MES										•					•
20	MES-BE															
21	Volatility															
22	Size conc.		•	•	•	•		•	•	•	•		•	•	•	•
23	Turbulence	•	•		•								•			
24	PQR															
25	Average DD.															
26	portfolio DD.															
27	MRI CITI Index															
28	CAPE	•	•	•	•	•	•	•	•	•	•			•	•	
29	VXO	•	•				•	•								
30	Sent. Index					•										
31	Credit-to-gdp gap															
32	Debt Service Ratio			•	•	•		•	•	•	•		•	•	•	•
33	Loan Supply								•							

Notes: The dots in the table refer to the indicators for which the associated coefficient $\beta_{i\tau}$ estimate (ie, its posterior median) is different from zero and therefore selected for inclusion in the quantile regressions for τ, at horizons h, in quarters. The regressions include a constant, two own lags of GDP growth and the Chicago Fed National Activity Index (CFNAI) which are not subject to variable selection and therefore always feature in the regressions and are not reported.

Table 2 shows the systemic risk indicators selected, from the set of all measures considered, for a given quantile τ and prediction horizon h. The quantile grid τ is chosen in line with the literature, to accurately depict the full predictive distribution of economic growth. A systemic risk indicator deemed relevant in explaining economic downturns is expected to be selected for the lower quantiles. Moreover, we consider three projection horizons h - one, four and eight quarters ahead. Thus, we can distinguish between indicators that signal future economic developments in the very short term and with some time in advance (up to two years). This is important for policy reasons as addressing risks with measures such as macroprudential policies might take some time.

Several messages can be taken from Table 2. First, systemic risk is relevant in predicting the distribution of economic growth - not only its central moment. However, less than halve of the indicators are selected as relevant predictors for any quantile τ considered in our exercise. This may reflect either an overall poor in-sample fit of many of the indicators considered or potential multicollinearity stemming from overlapping information that many of these measures contain. Second, systemic risk measures are expected to signal risks to growth and thus explain the lower tail of the predictive GDP growth distribution. However, even though quite a few indicators are useful in explaining lower quantiles of economic growth in the short-term (i.e, for $h = 1$), such predictability is not as evidently observed for longer-horizons. Remarkably, very few indicators are selected in the quantile regression for $\tau = 0.05$, four and eight quarters ahead.

Some indicators are picked up by the algorithm for most quantiles considered. The term spread, debt service ratio, the measure of size concentration in the financial sector and the Cyclical Adjusted Price-to-Earning ratio (CAPE) stand out as being consistently relevant. Several other measures such as the VXO, the Moody's Baa/Treasury spread, the mortgage and commercial paper spreads are selected for some horizons and quantiles considered. Nevertheless, many systemic risk measures are rarely selected. The question of whether this reflects a high degree of collinearity with other indicators which deliver superior fit or irrelevance in predicting real economic developments cannot be answered in this framework.

It is also possible to distinguish between systemic risk indicators that tend to be relevant in the short term, up to one year ahead, and those that signal risks to growth in the medium run, for h=8 quarters. The term spread, the concentration index and the Debt Service Ratio are relevant across quantiles and forecast horizons. While the CAPE, the VXO and a series of credit spreads seem to help forecast lower quantiles of economic growth mostly in the short-term.

4.1 Robustness

It has been noted that SSVS recovers a pattern of sparsity which is only valid provided that the true model is actually sparse (see Giannone et al. (2017)). It is therefore prudent to examine how sensitive the results presented so far are to the specific shrinkage technique used. To do so, we employ the additional methods discussed - the Bayesian Lasso and the Ridge. Table 3 summarizes the main findings. The coefficients signalled as relevant are those that significantly differ from zero -

at least 50 % of the posterior density around the median does not include zero. This calculation is done for comparison purposes, since contrary to the SSVS, both the Ridge and the Bayesian Lasso deliver continuous posterior distributions. The shrinkage performed by the Ridge and the Bayesian Lasso differs from the SSVS for some of the most relevant systemic risk indicators.

The first columns in Table 3 correspond to the SSVS results and show the main findings previously discussed, that features in Table 2, for a forecasting horizon of four quarters. Whereas, the next columns show the indicators found to be relevant when re-running the model with the Bayesian Lasso and Ridge priors. The indicators deemed relevant are quite consistently signalled by the alternative methods employed. Some differences can however be observed. Compared to the SSVS prior, the Bayesian Lasso and Ridge select more systemic risk indicators as relevant covariates to explain the lower quantiles of GDP growth considered.

Overall, the main result that only a select few systemic risk indicators contain additional relevant information in predicting future economic developments holds across both sparse and dense methods. The most relevant predictors selected which include the term spread, the CAPE, size concentration of the financial sector and the Debt Service Ratio are consistently relevant in all alternatives. Nevertheless, both the Bayesian Lasso and the Ridge tend to favour the inclusion of some indicators that have not been selected in our baseline SSVS quantile regression. Loan supply, the mortgage spread and the commercial paper spread are examples of such indicators. The VIX/VXO is also consistently favoured by both alternative shrinkage techniques.

Table 3: Systemic Risk indicators selected as relevant in explaining different quantiles of the predictive distribution of GDP growth, one year ahead.

		SSVS					Lasso					Ridge				
#	Systemic risk indicator	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.75$	$\tau = 0.95$	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.75$	$\tau = 0.95$	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.75$	$\tau = 0.95$
1	absorption		•										•			
2	Delta Absortion															
3	AIM															
4	CatFin															
5	GZ spread															
6	Baa/Aaa Bond yield														•	
7	TED spread															
8	Term Spread		•	•	•	•	•	•	•	•	•	•	•	•	•	•
9	Baa/10-yr T-rate spread				•	•				•	•				•	•
10	Mortg-GS10 Spread						•	•	•	•		•	•	•		
11	Comm. paper-3mT-Bill spread		•				•	•	•	•	•	•	•	•	•	•
12	Excess Bond Premium									•						
13	Intl. Spillover								•							
14	CoVaR		•	•		•		•	•					•		•
15	Delta CoVaR					•			•							•
16	Book lvg.					•				•	•				•	•
17	Mkt. Lvg.															
18	DCI															
19	MES					•										•
20	MES-BE															
21	Volatility															
22	Size conc.		•	•	•	•	•	•	•	•	•		•	•	•	•
23	Turbulence						•				•	•	•			•
24	PQR															
25	Average DD.															
26	portfolio DD.															
27	MRI CITI Index															
28	CAPE	•	•	•	•	•	•	•	•	•	•	•	•	•	•	
29	VXO	•	•				•	•	•			•	•	•		
30	Sent. Index									•			•		•	•
31	Credit-to-gdp gap								•							
32	Debt Service Ratio		•	•	•	•	•	•	•	•	•	•	•	•	•	•
33	Loan Supply			•			•	•	•	•			•	•	•	

Notes: The dots in the table refer to the indicators selected by the quantile regressions with a SSVS, Lasso and Ridge priors. For the Lasso and Ridge the signalled indicators are those for which at least 50 % of the posterior density around the median does not include zero. The quantile regressions results are for τ and for the horizons h in quarters.

4.2 Time-variation in relevance of Systemic Risk Indicators

We now examine whether the predictive relationships found in previous sections are stable over time. Given that our main interest throughout the paper is in the lower tail of economic growth, we will conduct our discussion in this section with the results of the quantile regression estimated with a SSVS prior for $\tau = 0.25$.[10] We re-estimate our model on a rolling-window of 60 quarters (covering roughly 3 times the average NBER business cycle length, from peak to trough, excluding the Covid Recession).

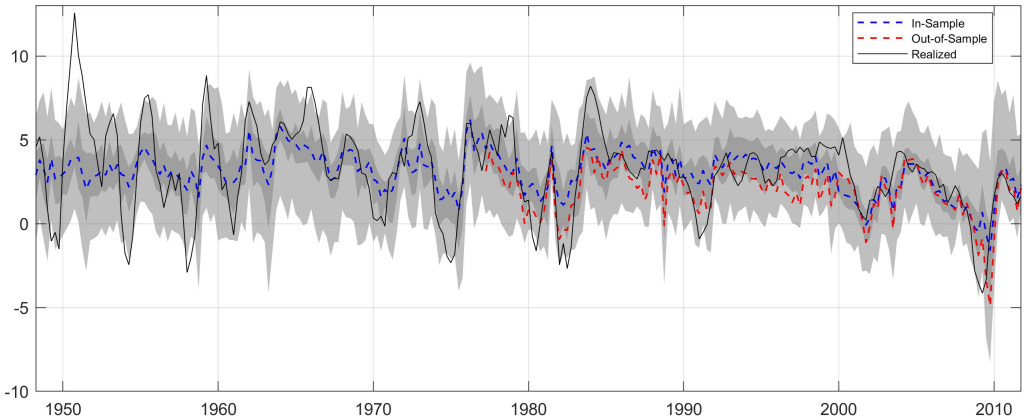
Figure 3 summarizes the key results of our rolling-window forecasting exercise. The heatmaps show the posterior of γ for each systemic risk indicator, often dubbed in the literature Posterior Inclusion Probability (PIP), for the forecasting exercise conducted one-quarter, four-quarters and eight-quarters ahead. The findings suggest that, similar to the full-sample results, many more systemic risk indicators are selected as relevant predictors of the lower tail of GDP growth in the short-term (one-quarter ahead) as compared to medium-term prediction horizons. We also observe that the term-spread notoriously stands out as one of the most significant predictors, relevant for all forecasting horizons considered. However, these results seem to suggest that the term-spread may have lost predictive power in more recent periods. In fact, the PIP of the term spread suggests this indicator is not selected for regressions estimated from the year 2000, onwards. Whereas, in more recent periods, the VXO and the CAPE seem to be the most relevant predictors. Other indicators, which are not selected in the full-sample estimation exercise are occasionally selected on a rolling window basis (eg. the GZ Spread). However, their PIP points towards an unremarkable and feeble predictive power.

4.3 Forecasting Economic Growth with Systemic Risk indicators

In this section, we evaluate the (pseudo) out-of-sample forecasting performance of the quantile regression methods discussed. We re-run the model recursively on a training sample of data between 1947Q1 and 1976Q1, using the latest vintage of data. While it would be interesting to study the real-time forecasting performance of our model, most of the predictors are not available in real-time. At each out-of-sample point, we predict GDP growth for a given quantile τ, at a given horizon h, using the full set of systemic risk indicators deemed relevant by the SSVS model. We then compare our prediction with the observed value of GDP growth and the in-sample estimates. This procedure is then iterated, expanding the estimation sample one period at a time, until the end of the sample (2011Q4). Figure 2 summarize the main output of this exercise, comparing the in-sample fit of the median ($\tau = 0.5$) and remaining upper/lower quantiles τ considered, with the out-of-sample prediction of the median obtained by re-estimating the model recursively at each out-of-sample point in time.

[10] Mindful of the potential risks to estimators of estimating extremal quantiles with small samples of data we conduct our discussion with the results of $\tau = 0.25$ instead of $\tau = 0.05$.

Figure 2: Forecasting quantiles of GDP growth, 1-year ahead



Notes: In-sample time series of $\mathbb{Q}_{\tau=0.5}(y_t|I_{t-h})$, where $h = 4$ in quarters and its out-of-sample counterpart which is obtained recursively by re-estimating the model on an initial training sample up to 1976Q1, updated for each quarter thereafter. The shaded area represent predictive quantiles. The dark grey area characterize the interquartile range and the light grey the distance between the 5th and 95th quantiles of GDP growth estimated on the full sample.

In-sample estimates do not differ very significantly from out-of-sample prediction for the median, although some differences can be observed at the beginning of the out-of-sample period between 1976Q1 until 1990Q1 for the prediction and for the period marked by the Great Recession. It is also possible to observe that the realized GDP growth is within the 5th-95th percentile range, for most observations. There are however some exceptions, most noticeably at the beginning of the sample and interestingly during recessions.

Next, we evaluate the accuracy and calibration of the quantile forecasts following closely Brownlees and Souza (2021). While Figure 2 reports quantile forecasts for the model estimated with a SSVS prior, we now comprehensively assess the forecasting properties of all models employed throughout the paper by defining three evaluation statistics. The average empirical coverage is defined as

$$C = \frac{1}{T}\sum_{t=1}^{T} \mathbb{1}_{\{y_t > \mathbb{Q}_\tau(y_t|I_{t-h})\}}, \tag{13}$$

and measures the accuracy of the quantile forecasts for a given τ. Accurate predictions are expected to have an empirical coverage or 'hit rate' close to the nominal coverage. In addition, we define average lengths of the predictions as

$$L = \frac{1}{T}\sum_{t=1}^{T} \hat{Q}_\tau(y_t) - \mathbb{Q}_\tau(y_t|I_{t-h}). \tag{14}$$

Where $\hat{Q}_\tau(y_t)$ denotes the (unconditional) τ-th empirical quantile. Quantile forecasts with smaller average lengths are preferred according to this criteria. Finally, we evaluate the quality of our quantile forecasts for different models on the basis of a loss function. The tick loss, which has been found to be a proper loss function to evaluate quantile forecasts by Giacomini and Komunjer (2005), can be defined as

$$TL = \frac{1}{T}\sum_{t=1}^{T} \rho_\tau(y_t - \mathbb{Q}_\tau(y_t|I_{t-h})). \tag{15}$$

Models delivering statistically significantly lower tick loss statistics are preferred. We evaluate the significance of the gains to forecasting in terms of tick loss by using Diebold-Mariano tests following Brownlees and Souza (2021).

Table 4 provides a summary of the in-sample and out-of-sample performance of all the models considered throughout the paper and compares them to a baseline quantile regression which does not include any of the systemic risk indicators discussed thus far. If the predictive content of systemic risk indicators is relevant in forecasting the different quantiles of economic growth, then one would expect to see any of the alternative models consistently outperform this baseline specification.

The model QR(baseline) is a standard autoregressive Bayesian quantile regression for GDP growth which only includes a constant, own-lags and the Chicago Fed National Activity Index (CFNAI). The last variable is included in an effort to purge any information included in systemic risk indicators related to real activity which may help forecast economic growth. The alternative specifications include the QR-SSVS, QR-LASSO and QR-Ridge. These models are estimated on an augmented version of the data with which the QR(baseline) is fitted (i.e. they include all systemic risk indicators discussed in previous sections). For each different model, the three statistics - average empirical coverage, average lengths and tick loss, are computed for a given quantile τ and forecast horizon h.

The table carries two important results. First, evidence favours the view that the inclusion of systemic risk indicators improves the quality of quantile forecasts of economic growth. This result can be observed by comparing the tick loss for any alternative specification with the baseline quantile regression which does not include systemic risk indicators. With rare exceptions, alternative models deliver superior quantile forecasts of GDP growth. The result is more pronounced in-sample. However, out-of-sample estimates corroborate this result. Second, average empirical coverage statistics suggest that, in general, all models deliver comparably accurate quantile forecasts. However, alternative specifications do not seem to be superior in this instance. It is possible to observe that all models tend to perform better in-sample as compared to out-of-sample. In particular, the alternative specifications which include systemic risk indicators tend to overestimate economic downturns and economic expansions. For instance, the average empirical coverage statistics for $\tau = 0.05$ is 1 for many models, across forecast horizons. Whereas, for $\tau = 0.95$ this statistics is often very small, close to zero.

Table 4: In-Sample and Out-of-Sample Statistics

	In-Sample														
τ	0.05			0.25			0.5			0.75			0.95		
statistic	C	L	TL	C	L	TL	C	L	TL	C	L	TL	C	L	TL
h=1															
QR(baseline)	0.95	-1.05	0.38	0.75	0.09	1.05	0.51	-0.06	1.3	0.25	0.11	1.04	0.04	1.00	0.4
QR-SSVS	0.94	-2.26	0.31***	0.76	0.20	0.91***	0.53	0.06	1.16***	0.27	0.47	0.93***	0.05	1.47	0.34***
QR-LASSO	0.98	-1.57	0.28***	0.77	0.2	0.85***	0.51	0.02	1.11***	0.23	0.14	0.89***	0.02	0.46	0.34**
QR-RIDGE	0.97	-1.6	0.29***	0.76	0.2	0.88***	0.52	-0.03	1.13***	0.23	0.24	0.91***	0.04	1.09	0.35**
h=4															
QR(baseline)	0.95	-0.27	0.26	0.76	-0.14	0.82	0.51	-0.04	0.95	0.26	0.02	0.76	0.04	0.17	0.25
QR-SSVS	0.94	-1.35	0.22***	0.78	-0.15	0.62***	0.53	0.22	0.76***	0.29	0.46	0.61***	0.07	0.94	0.23***
QR-LASSO	0.99	-0.95	0.2***	0.77	-0.13	0.57***	0.49	0.11	0.72***	0.22	0.11	0.58***	0.02	0.06	0.22*
QR-RIDGE	0.98	-0.94	0.21***	0.77	-0.13	0.59***	0.51	0.10	0.74***	0.24	0.18	0.59***	0.04	0.32	0.23**
h=8															
QR(baseline)	0.96	0.11	0.2	0.75	-0.06	0.61	0.50	0.00	0.73	0.25	0.00	0.57	0.05	-0.04	0.19
QR-SSVS	0.97	-0.47	0.15***	0.75	-0.36	0.42***	0.53	0.24	0.53***	0.32	0.51	0.42***	0.04	0.57	0.16***
QR-LASSO	1.00	-0.2	0.15***	0.79	-0.32	0.37***	0.53	0.17	0.48***	0.20	0.25	0.39***	0.01	-0.36	0.17
QR-RIDGE	0.98	-0.27	0.15***	0.78	-0.3	0.39***	0.50	0.17	0.5***	0.23	0.27	0.41***	0.02	0.11	0.18
	Out-of-Sample														
τ	0.05			0.25			0.5			0.75			0.95		
statistic	C	L	TL	C	L	TL	C	L	TL	C	L	TL	C	L	TL
h=1															
QR(baseline)	0.99	-0.3	0.35	0.81	0.36	0.83	0.45	0.24	0.97	0.09	0.73	0.84	0.01	0.76	0.35
QR-SSVS	1.00	-1.31	0.28***	0.78	-0.14	0.57***	0.47	0.41	0.74***	0.13	1.42	0.63***	-	0.61	0.32
QR-LASSO	1.00	-1.31	0.28***	0.78	-0.14	0.57***	0.47	0.41	0.74***	0.13	1.42	0.63***	-	0.61	0.32
QR-RIDGE	1.00	-1.65	0.26***	0.77	-0.17	0.58***	0.45	0.38	0.77***	0.15	1.50	0.65***	0.01	1.16	0.29*
h=4															
QR(baseline)	0.96	0.06	0.24	0.75	0.24	0.65	0.36	0.14	0.75	0.06	0.10	0.67	-	0.27	0.23
QR-SSVS	0.96	-1.12	0.2***	0.73	-0.02	0.44***	0.40	0.59	0.56**	0.16	1.06	0.47***	0.01	0.85	0.21***
QR-LASSO	1.00	-0.1	0.22**	0.79	0.25	0.41***	0.45	0.68	0.52**	0.11	0.95	0.46***	-	-0.24	0.26
QR-RIDGE	1.00	-0.46	0.2***	0.75	0.2	0.41***	0.47	0.66	0.52**	0.12	1.02	0.45***	0.01	0.32	0.23
h=8															
QR(baseline)	0.93	0.15	0.2	0.69	0.09	0.61	0.33	0.03	0.68	0.09	0.07	0.55	-	-0.17	0.19
QR-SSVS	1.00	1.17	0.18	0.83	0.23	0.3***	0.40	0.80	0.39**	0.16	1.05	0.34***	0.01	-0.06	0.18
QR-LASSO	1.00	1.79	0.21	0.89	0.4	0.31***	0.47	0.89	0.38**	0.15	1.08	0.34***	-	-0.71	0.21
QR-RIDGE	1.00	1.17	0.18	0.83	0.23	0.3***	0.40	0.80	0.39**	0.16	1.05	0.34***	0.01	-0.06	0.18

Notes: Empirical coverage, Length and Tick Loss are computed for each quantile τ and forecast horizon h for each model considered. The QR(baseline) is a standard Bayesian quantile regression, estimated with a constant, two own-lags of GDP growth and the Chicago Fed National Activity Index (CFNAI). The QR-SSVS, QR-LASSO and QR-RIDGE consider in addition all the systemic risk indicators discussed. The Diebold-Mariano statistics refer to the hypothesis of superior predictive ability of the tick loss of each alternative model *vis-à-vis* the baseline quantile regression. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5 Conclusion

This paper studies the link between real economic growth and systemic risk in light of a Bayesian quantile regression model that captures the nonlinear nature of this relationship. The quantile regression employed yields a complex predictive growth distribution. We empirically assess the relevance of 33 systemic risk indicators to explain the full spectrum of the distribution of GDP growth and analyse the relevance of these indicators in improving forecasts of macroeconomic risk. To deal with a large number of possible predictors, we employ sparse-modelling techniques to perform variable selection and shrinkage. These include the use of priors which implement Stochastic Search and Variable Selection (SSVS) and the Bayesian Lasso algorithms which are then compared to a Ridge which belongs to the class of dense methods. Describing the relation between systemic risk and real activity in a parsimonious way is motivated by statistical reasons - to avoid overfitting and unnecessary parameter proliferation; but it is also justified on economic grounds since earlier literature suggests that only a subset of systemic risk indicators are relevant in describing the interaction between systemic risk and economic growth. Understanding which particular indicator merits inclusion in the regression to explain the lower tails of the growth distribution, which we called growth fragility, is unclear a priori but important for two main reasons. First, it is essential to understand when and from which part of the financial system risks are originating. Secondly, from a statistical viewpoint, it is necessary to assess the predictive content of each systemic risk measure to understand its suitability as an early warning indicator of a recession. The SSVS prior is used to derive the main results and the alternative methods are used to analyse the sensitivity of the findings to the specific shrinkage technique employed.

In-sample results suggest systemic risk indicators add value in forecasting various quantiles of GDP growth. However, only a subset of these contain relevant information. Less than halve of the systemic risk indicators considered are selected as relevant predictors of lower quantiles of GDP growth, suggesting that most systemic risk indicators contain limited recession-relevant information. Nevertheless, some indicators stand out as relevant predictors of economic activity. The term spread, CAPE, the debt service ratio and the size concentration in the financial sector are consistently signalled as important when forecasting different quantiles of GDP growth. We study the stability of these results by re-estimating our model on a rolling-window basis. This exercise highlights the ephemeral nature of predictive relationships and suggests a loss of importance of the term-spread as a predictor of real activity in more recent periods. Nevertheless, taken-together evidence suggests systemic risk indicators help forecast GDP growth. The in-sample and out-of-sample quantile forecasts from models which include systemic risk indicators outperform those from a the model disregards such indicators.

Appendix A Data

Table 5: Data Description and Sources.

Series	Description	t-code	Source
GDPR	Real Gross Domestic Product.	5	St. Louis Fed
CFNAI	Chicago Fed National Activity Index, aggregates the most important real activity variables.	1	St. Louis Fed
absorption	Captures the fraction of the total variance of a set of assets explained or "absorbed" by a the first eigenvectors/principal components.	1	Giglio et al. (2016)
Delta Absortion	First difference of absortion.	1	Giglio et al. (2016)
AIM	The ratio of absolute stock return to dollar volume.	2	Giglio et al. (2016)
CatFin	Value at Risk measure of a cross-section of financial firms.	1	Giglio et al. (2016)
GZ spread	Corporate Bond credit spread calculated using secondary market prices of senior unsecured bonds issued by a large representative sample of US non-financial firms.	5	S. Gilchrist Website
Baa/Aaa Bond yield	Spread btw Moody's Seasoned Baa Corporate Bond Yield and 10-Year Treasury rate	5	St. Louis Fed
TED spread	The difference between 3M Treasury bill and 3M LIBOR based on US dollars.	1	Stock and Watson (2016b)
Term Spread	The difference between 10yr and 3M Treasury bill.	1	Stock and Watson (2016b)
Baa/10-yr T-rate spread	The spread between Moody's Seasoned Baa Corporate Bond and the 10Yr Treasury bill.	1	St. Louis Fed
Mortg-GS10 Spread	The spread btw 30-Year Conventional Mortgage Rate and 10Yr Treasury bill.	1	Stock and Watson (2016b)
CP3FM-TB3MS	The spread btw 3-Month AA Financial Commercial Paper Rate and 3M Treasury bill.	1	Stock and Watson (2016b)
Excess Bond Premium	The residual component of the GZ spread that reflects investor attitudes toward corporate credit risk.	1	S. Gilchrist Website
Intl. Spillover	Cross-country comovement in a set of macroeconomic variables.	5	Giglio et al. (2016)
CoVaR	Value at Risk (VaR) of the financial system conditional on institutions being under distress.	1	Giglio et al. (2016)
Delta CoVaR	Derives from the CoVaR.	1	Giglio et al. (2016)
Book lvg.	Book leverage for the 20 biggest institutions in the US.	1	Giglio et al. (2016)
Mkt. Lvg.	Market leverage for the 20 biggest instututions in the US.	1	Giglio et al. (2016)
DCI	Number of Granger causal relationships between bank equity returns, as a measure of interconnectedness.	1	Giglio et al. (2016)
MES	A firm's expected equity loss when market falls below a certain threshold over a given horizon.	1	Giglio et al. (2016)
MES-BE	Derives from the MES.	1	Giglio et al. (2016)
Volatility	Average volatility of the equity returns of the 20 biggest financial firms in the US.	1	Giglio et al. (2016)
Size conc.	The market equity Herfindal index of the 100 biggest financial firms in the US.	1	Giglio et al. (2016)
Turbulence	Covariance relative to a longer-term covariance estimate of top US financial firms.	1	Giglio et al. (2016)
PQR	Principal Components of a set of systemic risk measures.	1	Giglio et al. (2016)
Average DD.	Average Distance to Default measures the market's perception of the average risk of insolvency among major US banks.	1	Cleveland Fed
Portfolio DD.	Portfolio Distance to Default measures the market's perception of the systematic insolvency risk of the banking system as a whole.	1	Cleveland Fed
MRI CITI Index	CitiBank Risk Aversion Indicator, aggregates a set of indicators capturing risk aversion in the financial markets.	1	Bloomberg
CAPE	Cyclical Adjusted Price-to-Earnings ratio, calculated as the ratio of the current price of the S&P500 by its inflation adjusted historical earnings record over the past 10 years.	5	R. Shiller's Website
VXO	Implied volatility of near-the-money options of the S&P500.	1	Bloomberg
Sent. Index	Stock Market Investor Sentiment Index.	1	J. Wurgler Website
Credit-to-gdp gap	Difference between the credit-to-GDP ratio and its long-term trend given in percentage points.	1	BIS, Data Warehouse
Debt Service Ratio	The ratio of interest payments plus amortisations to income for the private non-financial sector.	1	BIS, Data Warehouse
Loan Supply	Net Percentage of Domestic Banks Tightening Standards for Commercial and Industrial Loans to Large and Middle-Market Firms as reported by Senior Loan Officers.	1	St. Louis Fed

Notes: The transformation codes (t-code column) are 1:levels; 2:1st dif; 5:1st dif of the logarithm. The dependent variable y_{t+h} of the regressions presented represents the growth of GDP between periods t and t+h. It is calculated as the sum of the log difference of GDPR between t and t+h. Regressors are standardized to have mean zero and variance 1. Missing values stemming from different sample start dates are treated by setting them to zero.

Appendix B Algorithm for Posterior Inference

The model is based on the priors for the regression parameters and their variance as defined in the body of the paper and outlined below

$$\beta|\gamma,\delta \sim N(0,\gamma\delta^2)$$
$$\delta^{-2} \sim Gamma(a_0,a_1)$$

These priors are common to all three methods presented to perform model selection and shrinkage. The key parameter to enforce sparcity is γ and we define a hierarchical structure where the hyperprior distribution dictates which method from the three (SSVS, Bayesian Lasso or Ridge) is used. In what follows we present the conditional posteriors necessary to set up the Gibbs Sampler used for full posterior inference. To ease the notation, we drop the subscript τ from all parameters. However, it is important to note that the procedure described applies to each quantile and inference is based on estimation for a predefined quantile grid.

B.1 SSVS

A Stochastic Search Variable Selection Algorithm in a quantile regression setting is proposed by Korobilis (2017) based on the Gibbs Sampler of Kozumi and Kobayashi (2011). We follow the authors, define a grid and set the quantiles considered $\tau = \{5,...,95\}$ with increments of 5. In practice, each quantile defined gives rise to an additional regression to estimate. Thus parameters vary across quantiles τ. The following points describe a full pass-throw of the Gibbs Sampler, for each quantile τ.

1 The conditional posterior of β is given by

$$p(\beta|y,z,\delta^{-2},\gamma,\pi_0) \sim N(\bar{\beta},\bar{V}),$$
$$with \quad \bar{\beta} = \bar{V}\Big[\sum_{t=1}^{T}\tilde{x}_t(y_t-\theta z_t)/\phi^2 z_t\Big], \bar{V} = \Big[\sum_{t=1}^{T}\frac{\tilde{x}_t{}'\tilde{x}_t}{\tau^2 z_t} + diag(\gamma\delta^{-2})\Big].$$

2 The conditional posterior of δ^{-2} is given by

$$p(\delta^{-2}|y,z,\beta,\gamma,\pi_0) \sim Gamma(\bar{a_0},\bar{a_1}),$$
$$with \quad \bar{a_0} = a_0 + 1/2 \quad and \quad \bar{a_1} = \beta^2/2 + a_1.$$

Where a_0 and a_1 are hyperparameters that are set to 0.1.

3 The conditional posterior of z_t is given by

$$p(z_t|y,\beta,\gamma,\delta^{-2},\pi_0) \sim \mathcal{GIG}(\frac{1}{2},\bar{\kappa_0},\bar{\kappa_1}),$$
$$with \quad \bar{\kappa_0} = \sum_{t=1}^{T}(y_t - x_t\beta_\tau)/\phi \quad and \quad \bar{\kappa_1} = \sqrt{2+\theta^2}/\phi.$$

4 The conditional posterior of each element of γ is given by

$$p(\gamma|y,z,\beta,\delta^{-2},\pi_0) \sim Bernoulli(\pi_0).$$

5 The conditional posterior of π_0 is given by

$$p(\pi_0|y, z, \beta, \gamma, \delta^{-2}) \sim Beta(\bar{b_0}, \bar{b_1}),$$
$$with \quad \bar{b_0} = 1 + b_0 \quad and \quad \bar{b_1} = n - 1 + b_1.$$

Where b_0 and b_1 are hyperparameters that are set to 5 and 10, respectively.

B.2 Bayesian Lasso

The Bayesian Lasso has been proposed by Park and Casella (2008). Its implementation for quantile regression requires very few alterations to the Gibbs sampler previously characterized. The descriptions below entails the blocks of the SSVS algorithm that should be changed in order to achieve this specification.

1* The conditional posterior of β is given by

$$p(\beta|y, z, \delta^{-2}, \gamma, \pi_0) \sim N(\bar{\beta}, \bar{\Omega}),$$
$$with \quad \bar{\beta} = \bar{\Omega}\Big[\sum_{t=1}^{T} \tilde{x}_t(y_t - \theta z_t)/\phi^2 z_t\Big], \bar{\Omega} = \Big[\sum_{t=1}^{T} \frac{\tilde{x}_t{}'\tilde{x}_t}{\tau^2 z_t} + \Omega^{-1}\Big].$$

where $\Omega = diag(\gamma)$ is the prior variance for β.

4* The conditional posterior of each element j of γ is given by

$$p(\gamma_j|y, z, \beta, \delta^{-2}, \lambda) \sim \mathcal{GIG}(\frac{1}{2}, \mu, \lambda),$$
$$with \quad \mu = |\beta_j|\,.$$

5* The conditional posterior of λ is given by

$$p(\lambda_j|y, z, \beta, \gamma, \delta^{-2}) \sim Gamma(\bar{c_0}, \bar{c_1}),$$
$$with \quad \bar{c_0} = r \quad and \quad \bar{c_1} = \gamma_j/2 + \Delta.$$

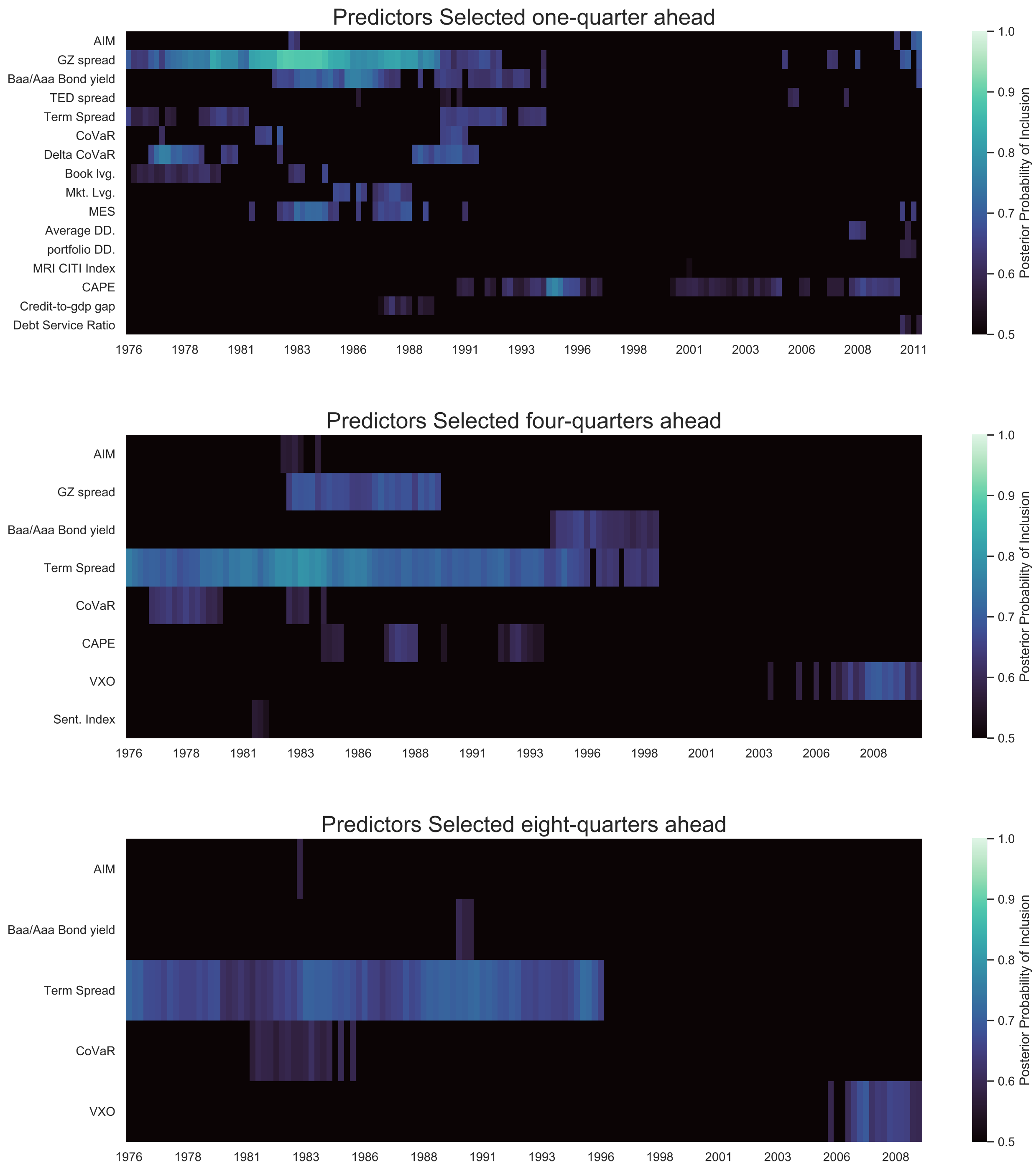
Where Δ and r are hyperparameters that are set to 1 and 1.78 respectively.

B.3 Ridge Regression

A Bayesian interpretation of the Ridge regression is licit and has been discussed in the literature (see Kapetanios et al. (2018); Giannone et al. (2017)). The Ridge regression can be viewed as a particular case of the SSVS model. Indeed, by simply setting $\pi_0 = 1$ the model estimated with a SSVS prior collapses into a Normal Gamma prior model (layers 4 and 5 are eliminated). This alteration is effortless and results in a model with Gaussian priors for the coefficients which has been shown to be equivalent to Ridge Regression.

Appendix C Additional Tables & Figures

Figure 3: Time-varying inclusion of Systemic Risk Indicators



Notes: Predictors selected one,four and eight-quarters ahead for inclusion in the quantile regression with an SSVS prior for $\tau = 0.25$ for the (pseudo) out-of-sample period between Q1-1976 and Q3-2011. Posterior Probabilities of inclusion are the mean of γ for those predictors selected to feature in the regression. Dark regions are those for which the respective predictor is not selected.

Appendix D Convergence Diagnostics

This subsection examines the convergence of the Markov Chain Monte Carlo in the baseline specification. Univariate regressions are less sensitive to starting points of the chain or size of the burn-in period. However, to make sure convergence is satisfactory, we compute inefficiency factors of β_τ. The table below shows these statistics for different quantile regressions employed, using the SSVS prior. These statistics are found to be lower that the inefficiency factors reported in Kozumi and Kobayashi (2011) and therefore acceptable.

Table 6: Inefficiency factors of the parameters of the Quantile Regression estimated with the SSVS prior.

#	Systemic risk indicator	$\beta_{j,\tau=0.05}$	$\beta_{j,\tau=0.25}$	$\beta_{j,\tau=0.50}$	$\beta_{j,\tau=0.75}$	$\beta_{j,\tau=0.95}$
1	absorption	9.95	1.76	1.13	1.83	4.19
2	Delta Absortion	1.63	2.09	1.10	1.24	1.45
3	AIM	7.97	1.71	2.97	2.28	3.29
4	CatFin	0.99	0.63	0.54	1.34	1.19
5	GZ spread	3.43	2.72	2.51	1.87	3.26
6	Baa/Aaa Bond yield	8.08	1.64	2.13	2.05	4.16
7	TED spread	3.31	1.28	1.57	2.89	5.66
8	Term Spread	1.91	1.49	1.13	1.31	4.54
9	Baa/10-yr T-rate spread	2.57	1.85	1.21	0.80	1.04
10	Mortg-GS10 Spread	2.83	1.92	1.42	0.89	2.06
11	Comm. paper-3mT-Bill spread	2.07	2.25	1.03	1.17	1.18
12	Excess Bond Premium	1.20	1.36	1.34	1.34	2.18
13	Intl. Spillover	6.16	2.63	2.57	2.59	4.24
14	CoVaR	8.08	3.34	2.34	4.54	9.50
15	Delta CoVaR	6.24	4.23	2.44	5.04	9.66
16	Book lvg.	3.39	1.94	1.13	1.75	5.43
17	Mkt. Lvg.	5.47	2.12	1.76	2.13	5.07
18	DCI	1.26	1.03	0.86	0.49	0.85
19	MES	9.64	2.80	2.33	2.70	6.28
20	MES-BE	0.91	0.85	0.86	0.91	0.31
21	Volatility	0.63	0.73	0.82	0.60	0.83
22	Size conc.	2.98	1.61	0.98	0.89	0.94
23	Turbulence	7.03	4.38	1.87	1.65	7.59
24	PQR	0.89	0.97	1.07	0.58	1.10
25	Average DD.	6.57	1.98	1.52	3.44	6.52
26	portfolio DD.	5.20	2.09	1.75	3.59	5.88
27	MRI CITI Index	5.92	1.81	1.00	3.12	6.27
28	CAPE	5.98	4.55	3.66	3.09	5.17
29	VXO	8.56	6.06	2.05	1.34	8.60
30	Sent. Index	3.25	2.58	2.01	2.20	5.59
31	Credit-to-gdp gap	4.40	2.82	1.60	2.31	9.11
32	Debt Service Ratio	4.97	3.08	2.01	3.28	5.78
33	Loan Supply	1.05	0.67	0.48	0.71	1.31

Notes: The inefficiency factors are calculated for a MCMC run of 5000 draws and 5000 burn-ins.

The inefficiency factors are a function of the infinite sum of the autocorrelation of the chain, which is estimated using a 4 % tapered window. It is commonplace to consider inefficiency factors equal or lower than 20 satisfactory.

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