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. We 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-modelling techniques that perform both model selection and shrinkage. Less than halve of the indicators considered are selected to explain lower tails of economic growth and instability of predictive relations is the norm.

JEL classification: G10, E37, C11, C32, C58.

Keywords: Quantile Regression, Systemic Risk, Growth Fragility, Forecasting.

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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. (2012a) 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 studies the relationship between output growth and systemic risk through the lens of a Bayesian quantile regression model. As opposed to the common approach in the literature, we use sparse-modelling techniques to address model uncertainty concerns, allowing for both model selection and shrinkage. We address two major challenges that complicate the study of this relationship. First, sys-

[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.

temic risk and real activity are thought to relate in a nonlinear way. For instance, Brunnermeier and Sannikov (2014) study the full dynamics of the equilibrium of an economy, characterized as inherently unstable due to nonlinear amplification channels that expose it to *volatility crisis episodes*. Because the system's reaction to shocks is nonlinear, even small shocks may be subject to amplification, pulling the economy away from its steady state. Moreover, the stationary distribution is bimodal, which in practice means the economy might remain persistently in a depressed regime due to endogenous risk. One step further, Christiano et al. (2014) augment a dynamic general equilibrium model with a financial accelerator mechanism and suggest that fluctuations in the severity of information asymmetry in the economy account for a material portion of business cycle fluctuations. Contrary to the extant literature, risk shocks stemming from the cross-sectional idiosyncratic uncertainty in the allocation of capital are not a mere propagation channel but the source of economic fluctuations. Consistent with these ideas, Adrian et al. (2019) model the full distribution of GDP growth that is found to be skewed and exhibit a long lower tail. Furthermore, financial conditions are found to determine downside growth vulnerability.

Second, any attempt to empirically model the link between systemic risk and real economic activity must deal with inherent model uncertainty plaguing such an exercise. On one hand, there are multiple dimensions of systemic risk and it is unclear which dimension is relevant in explaining each quantile of macroeconomic fluctuations. On the other hand, measurement error associated with each systemic risk measure might mean some indicators are too noisy and uninformative. In practice, the researcher is forced to choose a single set of regressors within the possible 2^K candidate models, supposing there are K different systemic risk measures from which to choose[3]. Adrian et al. (2019) and Giglio et al. (2016) deal with the large number of possible predictors by employing dense modelling techniques. The finan-

[3]The 33 systemic risk measures surveyed in this paper result in over 10^9 potential candidate models to choose from when relating systemic risk to real activity.

cial conditions index used by Adrian et al. (2019) is simply a linear combination of a large set of financial variables. Whereas, Giglio et al. (2016) explicitly uses principal component analysis to shrink the space of potential predictors within a quantile regression. The authors examine the predictive content of 19 different systemic risk indicators in explaining the lower tail of the predictive distribution of output, one year ahead. They find that systemic risk skews the distribution of real activity, shifting its left tail outwards.

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. The main disadvantage of this framework has to do with interpretability. 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. Instead, we examine the relevance of 33 of the most popular systemic risk indicators proposed in the literature in light of two sparse-modelling methods that deal with model uncertainty. 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. To understand the sensitivity of our results to the degree of shrinkage imposed, we re-run the model with a Bayesian Lasso prior suggested by Park and Casella (2008) and a Ridge prior type following Giannone et al. (2017).

Our approach has several advantages that allow us to study new questions that have not been addressed in the literature so far. First, by employing quantile regression methods, we explore the nonlinear nature of the relationship between output

[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.

growth and systemic risk. Quantile regressions yield complex predictive distributions that need not be symmetric and unimodal. Our approach is flexible enough to examine how the link between the two variables changes across quantiles. Second, we assess the empirical relevance of 33 systemic risk measures in a common setting, avoiding over-fitting and model dimensionality constraints. Third, we perform in-sample and out-of-sample analysis through a rolling window forecasting exercise to understand which systemic risk measures carry relevant information content for real activity at each point in time.

From an econometric point of view, the novelty of this work lies in the variable selection and shrinkage algorithms, that select the most relevant systemic risk indicators in explaining each quantile of output growth in a data-driven way. We show how the SSVS, Lasso and Ridge Quantile Regressions can be obtained in a common setting with few changes in the model specification. In addition, we build on Kozumi and Kobayashi (2011) and Korobilis (2017) and extend the Bayesian Lasso to allow for data-dependent shrinkage in a quantile regression environment.

The exercise offers some insights on the relevance of financial variables in macroeconomic prediction. A number of papers have 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)). Giglio et al. (2016) finds that few systemic risk measures possess significant predictive content for downside quantiles of macroeconomic shocks. D'Agostino et al. (2006); Bordo and Haubrich (2008) and others find that the yield curve is loosing importance as a driver of real economic developments. Two main results emerge from our exercise and contribute to this strand of the literature. First, less than halve of the indicators considered are selected to explain lower tails of growth. Systemic Risk indicators are expected to signal macroeconomic risks and predict growth fragility. However, the number of indicators selected as relevant predictors of lower tails of GDP are no more than those selected as relevant covariates of middle and upper quantiles. Out-of-sample analysis suggests systemic risk indicators improve economic growth forecasting occasionally but these pockets of predictability are rare and short-lasting. This result is in line with and extends the findings of Stock and Watson (2003). Second, from the 33 systemic risk measures assessed, the Term Spread, Commercial Paper spread, the Debt Service Ratio ,the measure of Loan Supply and a measure of size concentration in the financial sector are the most relevant predictors, chosen by the algorithm as containing relevant information to forecast GDP growth across quantiles, forecast horizons and shrinkage methods for the full sample. However, when performing a Rolling Window forecasting exercise we find that the Term Spread's forecasting power diminishes (post-1995). This result lends support to the hypothesis that the yield curve is loosing importance as a driver of real economic developments, as suggested by D'Agostino et al. (2006); Bordo and Haubrich (2008) and others.

The remainder of the paper proceeds as follows. Section 2 presents the data and section 3 reviews the literature on the 33 systemic risk indicators assessed. Section 4 explains the econometric framework, estimation technique, variable selection and shrinkage procedure. Section 5 discusses the main results and findings. Section 6 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. (2012b) 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 Absorption	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	Simon Gilchrist et al. (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	Simon Gilchrist et al. (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 the next section we explain each measure considered.

3 An overview of Systemic Risk indicators

In what follows, we briefly discuss each systemic risk measure covered by this article, grouping them by category, according to their characteristics. A thorough review is provided by Bisias et al. (2012b) and Giglio et al. (2016) and readers are referred to these articles for further details.

3.1 Institution specific risk

Institution specific measures of systemic risk capture entity-level financial stress. In contrast to macroeconomic systemic risk indicators, their level of granularity allows for a microeconomic view of systemic risk. It is the case of the CoVaR and ΔCoVaR of Adrian et al. (2019) that expresses the contribution of each financial institution to the overall risk in the system by measuring the loss stemming from the distress of a specific institution. Next, the MES - Marginal Expected Shortfall as proposed by Acharya et al. (2017), measures the conditional expectation of a firm's equity loss, given that the market falls below a pre-determined threshold, at a given horizon. A number of measures proposed in the literature follow the same logic, and are nested in the MES. This is the case of the SRISK of Acharya et al. (2012), the LRMES of Acharya et al. (2017) and others. With regards to financial institution liquidity risk, Amihud (2002) proposes the AIM - the ratio of absolute stock return to dollar volume. Another class of models focus on interdependence of equity returns of financial institutions. These include the Absorption ratio and its sibling, the delta Abortion, of Kritzman et al. (2011) that measure the portion of variance of the financial system explained by the first principal component. The International Spillover Index of Diebold and Yilmaz (2009) captures cross-country comovement in Macroeconomic variables. The Dynamic Causality Index - DCI of Billio et al. (2012) also focuses on entity level equity returns as a source of systemic risk. The authors measure the number of Granger causal relationships between bank equity returns, as a measure of interconnectedness. In addition to the aforementioned off-the-shelf systemic risk measures, Giglio et al. (2016) construct Book and Market leverage and volatility for the 20 largest US financial institutions. The authors also calculate the size concentration of the US financial sector using an Hirschman-Herfindahl index. Saldias

(2013) proposes to measure systemic stress by calculating the average distance-to-default of the banking system, that reflects the market implied insolvency risk of the US banking system. The author complements this measure with the portfolio distance-to-default that signals systematic insolvency of the financial system that is regarded as a portfolio of banks. These measures are calculated by using market prices of options on Exchange-Traded-Funds (ETFs) tracking the banking system.

Each entity specific measure of systemic risk discussed is included in our analysis by aggregating it across institutions.

3.2 Macroeconomic measures of Systemic Risk

Macroeconomic measures of systemic risk comprise those that are not specific to any institution in particular. It is the case of the CatFin of Allen et al. (2012) that takes a holistic approach by measuring the Value at Risk of the overall financial system. The Cyclical Adjusted Price-to-Earning ratio of Shiller (2005) is used to gauge the relationship between price and valuation of equity markets across the business cycle. The cycle described by the ratio of price to earnings of stock market constituents on aggregate reaches its peak before financial crises. Another example of such measures are those related to sentiment. The MRI CITI index is a risk aversion index, constructed by Citi Bank that summarizes the dynamics of key variables that determine risk aversion in the financial markets. These include the implied volatility of options on foreign exchange related assets, Emerging Market sovereign yield spreads, corporate CDS spreads, the implicit volatility of equity options and an interbank market spread. The case for considering risk aversion as a measure of financial imbalances is made by Adrian et al. (2010) who stress the key role of movements in the price of risk in determining the build-up and unfolding of financial imbalances. The main argument is that, when the price of risk changes, so does the risk bearing capacity of financial intermediaries. Therefore, risk appetite determines credit supply decisions and consequently potential financial imbalances.

The VIX is one of the most widely used measures of risk aversion (see Rey and Evgenia (2015) Baskaya et al. (2017)) and it has been related to bank risk-taking, international capital flows, leverage and credit cycles[5]. The sentiment index of Baker and Wurgler (2006) is also considered for reasons analogous to those explained above. The authors document that their sentiment index explains financial market valuation across the business cycle. The last indicator related to sentiment is the Excess Bond Premium (EBP) of Gilchrist and Zakrajšek (2012). This indicator is interpreted by the authors as a measure of credit market sentiment or risk appetite in credit markets. Analytically, it is constructed as the residual component of their corporate bond market spread (GZ Spread), net of expected defaults.

Credit has been found to play an important role in triggering financial crises (see Jordà et al. (2011); Schularick and Taylor (2012); Jordà et al. (2015); Schularick and Taylor (2012). In fact, recent research by Dell'Ariccia et al. (2012) suggests that since the 1970s one out of three credit booms resulted in a financial crisis. Motivated by this evidence, our analysis comprises the credit-to-GDP gap - that measures the macroeconomic significance of the amount of debt contracted and the Debt Service Ratio, that reflects the debt burden of all agents in the economy. Some evidence presented by Aldasoro et al. (2018) suggests that these indicators signal forthcoming banking crises. We supplemented these measures with a Loan Supply indicator, that is taken from the Senior Loan Officer Opinion Survey, a quarterly survey on US bank lending practices carried out by Federal Reserve Banks. The macroeconomic significance of this series is discussed in Lown and Morgan (2006).

The last category of systemic risk indicators considered are various yield spreads. There is a large strand of early literature documenting the predictive content of the term spread (given by the slope of Treasury yields) in forecasting economic downturns in the medium-term horizon (for instance Estrella and Hardouvelis (1991),

[5]We include the VXO which is similar to the VIX except that the underlying index from which it derives its value is narrowed down to a smaller set of firms. This is to avoid the structural break in the VIX series resulting from the change in basis for its calculation.

Estrella and Mishkin (1998), Stock and Watson (2003) and Piazzesi et al. (2006)). Term spreads are thought to aggregate a large amount of recession-relevant information in the economy. On one hand, they are forward looking variables, summarizing expectations of economic agents about the future economic outlook. On the other hand, they reflect the current stance of monetary policy which is a powerful tool steering the business cycle. In addition to the term spread, we include in our analysis the TED spread, given by the difference between the 3-month LIBOR and the Treasury Bill yield for the same maturity.

Beyond term spreads, recent research has examined the importance of other yield spreads as leading indicators of future economic conditions. The information content of corporate bond spreads for the US and European countries' real economic activity has been studied by Gilchrist et al. (2009), Gilchrist and Zakrajšek (2012), Bleaney et al. (2016) and López-Salido et al. (2017). There are two main channels explaining the predictive power of credit spreads emphasized in the literature.

First, a part of credit spreads is due to default risk. Investors demand a premium for the likelihood of default of bond issuers. Hence, changes in the default premium are reflected in corporate yield spreads thus signalling future macroeconomic conditions. Second, it has been found that the part of corporate yield spreads, that is unrelated to default risk, may help predict economic activity. This component is often referred to as credit market sentiment, translating investor beliefs and the stance of credit supply. Why might credit market sentiment be a leading indicator of real activity ? Two main arguments justify this relationship. The first one is related to investor sentiment. The main idea is that investors price-in noisy news about the financial condition of borrowers when only a part of it reflects economic fundamentals. The noise component generates volatility in credit spreads as investors update their beliefs with regards to credit risk as new information becomes public. Second, credit spreads mirror changes in credit supply. Changes in the willingness to lend by major financial institutions result in tighter lending standards and less favourable financial conditions that exert a negative shock on economic activity, consistent with the financial accelerator mechanism pointed out by Kiyotaki and Moore (1997) and Bernanke et al. (1999).

The adage that credit spreads signal potential downturns in economic activity motivates the inclusion of a number of additional yield spreads in our analysis. We include the spread between Baa and Aaa Bond yields that summarize the price of risk at the end of Moody's rating spectrum of investment-grade corporate bonds. This series is popular and is used by López-Salido et al. (2017) in deriving their measure of credit market sentiment. Next, we include the Gilchrist and Zakrajšek (2012) spread (GZ spread), that is built using secondary market prices of senior unsecured bonds issued by large US non-financial firms. We supplement these measures by including the spread between the 30-year conventional mortgage rate, disclosed by Freddie Mac and the 10 year Treasury Bond yield. The spread given by the 3-Month AA Financial Commercial Paper Rate and the 3-Month Treasury Bill secondary market rate is also considered.

4 Bayesian Quantile Regression

We wish to explain the τth quantile of output growth h-steps ahead, 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 vector 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

$$\mathbb{Q}_\tau(y_{t+h}|I_t) = x_t'\beta_\tau + \varepsilon_t. \tag{3}$$

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 about 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 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

$$\mathbb{Q}_\tau(y_{t+h}|I_t) = x_t'\beta_\tau + \theta z_t + \phi\sqrt{z_t}u_t. \tag{5}$$

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

4.1 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 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.

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 shrinks 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.

4.1.1 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), 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 binomial variable vector, 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. On the other hand, since γ_τ is estimated from the data, within a standard Gibbs Sampler, examining the posterior of γ_τ will inform which variables are most relevant in explaining each quantile of real activity.

4.1.2 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))[6]. 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. Moreover, the authors show that the Laplace distribution can be written as a scale

[6] It works by solving the following optimization problem, $\beta^L = \text{argmin}_\beta \, \rho_\tau \varepsilon' \varepsilon + \lambda \left\| \beta \right\|_1$, 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.)

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.

4.1.3 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)).

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

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

4.2 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 C we assess the convergence of the Gibbs Sampler employed.

5 Discussion of the Results

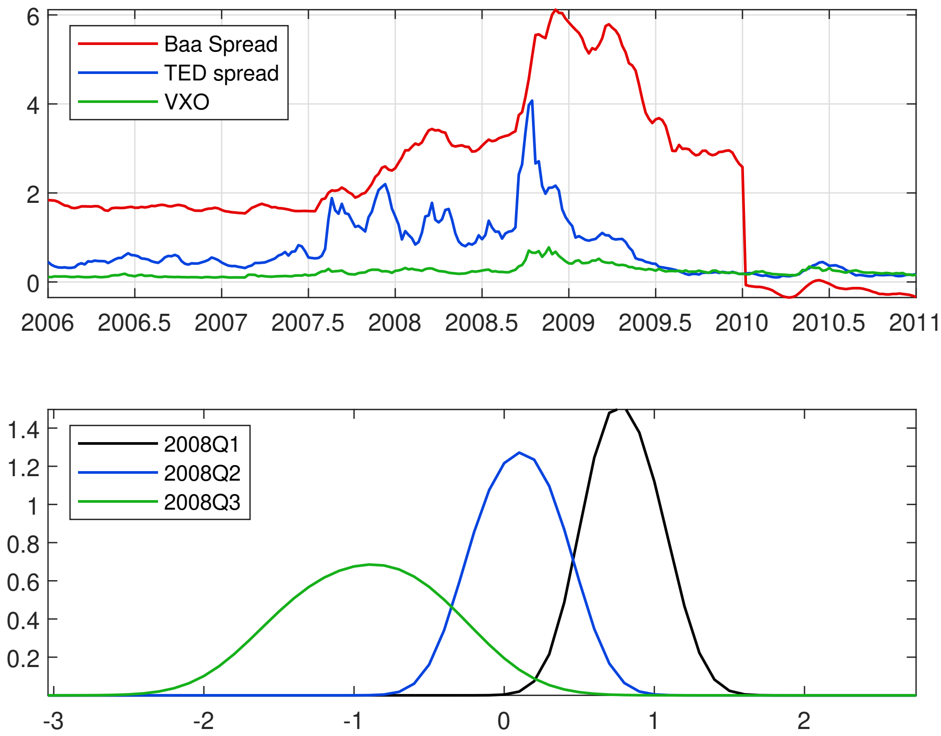
In this section we discuss the results that emerge from the estimation of the quantile regression which yields a predictive distribution of GDP growth, conditional on the set of systemic risk indicators considered. We focus on two main questions. First, which systemic risk indicators explain in-sample the variation of the lower tail of real activity, that is associated with recessions. Second, what is the out-of-sample performance of the various systemic risk measures proposed in the literature.

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 tails, since they reflect the likelihood of economic downturns. Figure 1 shows the predictive distribution of GDP growth for the three first quarters of 2008. The first quarter of 2008 marks the peak of the US business cycle and the start of a recession that ended the 73 month economic expansion that started in November 2001, bringing the Great Moderation to an end.

These dates are interesting because they mark the beginning of the Great Recession which followed a systemic financial crisis.

The first panel of Figure 1 shows three important measures of financial distress in the run-up to the 2008 recession, that are often regarded as harbinger of a crisis. In the second panel, the projected distribution of quarterly GDP growth (annualized) in 2008, one year ahead. The Figure suggests that systemic risk measures may have been relevant leads of GDP growth on this occasion, as they significantly increased some quarters before the onset of the recession. However, the predictive distribution of GDP growth in 2008Q1 is difficult to reconcile with the reality of a recession. Nevertheless, as we approach the recession, the model attributes greater likelihood to the scenario of an economic downturn. The projected distribution of GDP growth in 2008Q2 and 2008Q3 shows greater variance and exhibits a fat lower tail.

Figure 1: Predictive density of GDP growth and three measures of financial distress in the Great Recession.



Notes: The upper panel depicts the time series of three measures of financial distress - the Moody's Baa Corporate Bond Spread, the TED spread and the VXO. The lower panel plots the predictive density of GDP growth, computed 4 quarters ahead with a quantile regression with a SSVS prior for each element of $\tau = \{0.05, ..., 0.95\}$ and interpolated with a gaussian kernel. The conditional density of GDP growth is projected for the three first quarters of the NBER recession dates in 2008.

Which Systemic Risk indicators contain relevant information in predicting GDP growth? To answer this question we examine the indicators picked as relevant predictors of the full spectrum of the GDP growth distribution by the different shrinkage algorithms. The SSVS prior is our benchmark choice for implementing variable selection. It enforces sparcity by guaranteeing that only the most relevant variables are selected.

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

		predictors at horizon h = 1			predictors at horizon h = 4			predictors at horizon h = 8		
#	Systemic risk indicator	$\tau = 25$	$\tau = 50$	$\tau = 75$	$\tau = 25$	$\tau = 50$	$\tau = 75$	$\tau = 25$	$\tau = 50$	$\tau = 75$
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 for which the probability of inclusion (ie, the posterior mean of γ_p) is greater than 0.5 and therefore selected for the quantile regressions for $\tau = \{0.25, 0.5, 0.75\}$, for the horizons $h = \{1, 4, 8\}$ in quarters. The regression includes 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 and prediction horizon. The quantiles τ reported depict a lower $\tau = 0.25$, a middle $\tau = 0.5$ and upper $\tau = 0.75$. Hence, a systemic risk indicator deemed relevant in explaining economic downturns is expected to be selected for the lower quantile. In addition, we consider three projection horizons - 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, few systemic risk indicators are selected to explain the predictive distribution of GDP growth. This may reflect either an overall poor in-sample fit of some measures 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, results suggest that less than halve of the indicators considered are selected for inclusion in the lower quantile regression ($\tau = 0.25$). Systemic risk measures do not appear to contain information that predicts in specific growth fragility since the number of indicators that feature in the lower quantile regression is no greater than the number of measures selected to explain middle and upper quantiles. This highlights that predicting economic downturns such as recessions adds even more difficulty to the already challenging task of predicting middle quantiles of real economic growth.

Some indicators are picked up by the algorithm for all horizons and quantiles. It is the case of the Term Spread, Debt Service Ratio and the measure of size concentration in the financial sector. Several other measures such as the CAPE, Loan Supply, the VIX, the Moody's Baa/Treasury spread, the Mortgage and Commercial Paper spreads are selected for some horizons and quantiles considered. On the contrary, most systemic risk measures are rarely selected. This may reflect either a high degree of collinearity with other indicators which deliver superior fit or irrelevance in predicting real economic developments in the sample considered.

Systemic risk measures related to Debt and Credit in the economy, such as the Credit-to-GDP gap, the Debt Service Ratio and a measure of Credit Supply derived from the Senior Loan Officer Opinion Survey (Loan Supply) seem to be useful predictors of growth fragility in the medium run, up to 2 years. Whereas, other financial market indicators such as the market expectation of near term volatility (VXO) and the cyclical adjusted price to earning (CAPE) seem to be more relevant in the short run (up to 1 year ahead).

5.1 Robustness

To understand the extent to which the results presented so far change with respect to the specific shrinkage technique, we use the additional methods discussed - Bayesian Lasso and Ridge - and report the findings in Table 3. The first three columns show the main result previously discussed, that features in Table 2. While columns 4 to 9 show the variables selected by the Lasso and Ridge quantile regressions as relevant predictors of the distribution of GDP growth one year ahead. Unlike the posterior distribution for the coefficients in the SSVS case, which inherents a discountinuity in zero from the prior, concentrating a significant mass of probability, in the Lasso and Ridge case shrinkage occurs less vigorous. It is common for coefficients to be close, but not exactly zero. For comparison, Table 3 reports the coefficients that are significantly differ from zero as those for which 95 % of the posterior does not include zero and the absolute value of the coefficient represents more than 1 % of the standard deviation of the respective indicator.

Compared to the SSVS prior, The Bayesian Lasso selects less systemic risk indicators as relevant covariates to explain lower quantiles of GDP growth. In total, only 6 of such indicators are chosen by the algorithm out of the 33 eligible covariates to explain lower quantiles of the projected GDP growth distribution. On the contrary the Ridge prior selects 9 predictors. This compares with 9 variables selected by the SSVS. 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. In addition, the finding that indicators are not particularly useful in predicting growth fragility is also common across all methods.

The specific measures selected differ across methods. However, most predictors selected such as the term spread, the commercial paper spread, the size concentration in the financial sector, Debt Service Ratio and Loan Supply are consistently picked by all alternatives. Notoriously, the various measures of Debt and Credit in the economy which include the Debt Service Ratio and the Loan Supply are always selected, regardless of the specific shrinkage method used. The same is true for the Term Spread and the Commercial Paper Spread. These results are consistent with the literature documenting a well established relationship between various credit spreads and real economic activity (see Stock and Watson (2003) for a review of the literature on this subject).

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

#	Systemic risk indicator	Spike-and-Slab			Lasso			Ridge		
		$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$
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 the 95 % credibility interval for the associated coefficient does not include 0 and in addition the coefficient is greater than 1 % of the variable's standard deviation. The quantile regressions results are for $\tau = \{0.25, 0.5, 0.75\}$ and for the horizons $h = \{1, 4, 8\}$ in quarters.

5.2 Time-varying relevance of Systemic Risk indicators

One important limitation of our in-sample analysis is that it does not account for possible structural breaks affecting the parameters. In other words, full sample results are unable to capture potential changes in the relevance of individual variables across the full sample considered. This is important from an economic point of view because, each systemic risk indicator summarizes the information of a particular sector of the financial system, forcefully leaving out other pieces of information that might be more important in driving economic outcomes in some periods and less relevant in others. Each recession is characterized by its own idiosyncrasies. Therefore, it is natural that some systemic risk indicators are only relevant in some subset of the sample considered.

To examine this issue, we re-estimate the model over a rolling window of 60 quarters. The rolling sample length is chosen to include roughly 3 business cycles that last on average roughly 5 years [9]. In practice, we recursively re-estimate the model every quarter and perform variable selection. Figure 2 summarizes the results for the iterative estimation exercise, one year ahead. The graph shows which of the 33 systemic risk measures listed and numbered in Table 1 are automatically selected by the SSVS algorithm at each time period, for a quantile regression estimated for $\tau = 0.25$. The same exercise is also carried out for other quantiles and the results are reported in Figure 3 (Appendix D). The motivation to pay closer attention to the regression for a lower quantile is no different from the previous discussion. Systemic risk indicators should in particular predict lower tails of economic growth.

For a given quarter, the selected indicators are highlighted with a coloured ring. The colour of the ring is defined by the probability of inclusion of each variable, which is given by the posterior median of γ (see methodology section) should the variable be included. The probability of inclusion measures the likelihood that a given variable is selected by the algorithm within each Gibbs Sampler pass through. The closer it is to 1, the stronger the predictive content of each indicator.

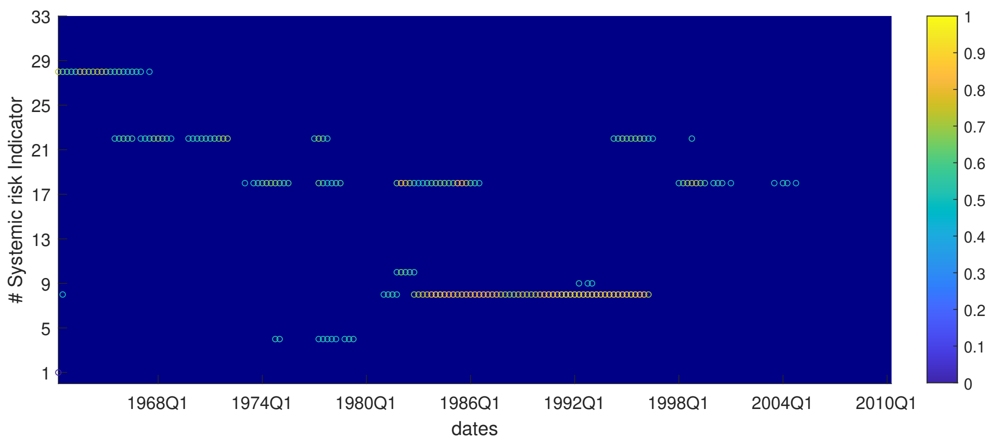
Some main results are worth highlighting. First, consistent with the finding previously discussed, systemic risk measures do not appear to add more value to prediction of lower quantiles of GDP growth as compared to middle quantiles, suggesting they are not more informative about economic downturns. Second, some

[9] According to the NBER's Business Cycle Dating Committee, between 1945 and 2009 there were 11 cycles.

systemic risk measures are selected more often than others. The most consistent measures picked are the term spread, which is selected 60 times in the recursive exercise out of 193 quarters between 1962Q1 and 2010Q1. The size concentration of the financial sector and the DCI are also commonly selected. On the contrary, most indicators are very rarely relevant as predictors of economic growth on a roughly 15 year rolling window.

Third, it is possible to observe that the term spread is consistently selected by the algorithm from the beginning of the sample until the 1996Q2 and stops being selected thereafter. This finding lends support to the result of many studies suggesting that the ability of the term spread to forecast output growth has diminished in recent years (see Paya et al. (2004); Haubrich and Michael D. Bordo (2004); D'Agostino et al. (2006); Bordo and Haubrich (2008)).

Figure 2: Systemic risk indicators selected as predictors of the 20th percentile of the predictive distribution of GDP growth, one-year ahead and respective probability of inclusion.



Notes: The dots in the heat-map refer to the indicators for which the average probability of inclusion (ie, the posterior mean of γ_p across intervals of p) is greater than 0.5 and therefore selected on a rolling window of 60 quarters, one-year ahead. The colour of the rings depict the average probability of inclusion of each indicator, for each period. The regression includes 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.

5.3 Forecasting Output Growth using Systemic Risk indicators

The pseudo out-of-sample statistics presented in Table 4 are based on forecasts of GDP growth computed by augmenting an AR(2) model with each systemic risk indicator considered. The idea of this exercise is to understand if the inclusion of a given indicator improves the forecasting performance of a random walk model. The Root Mean Square Forecast Error (RMSFE) of this forecast is then compared to the baseline AR(2), which is the benchmark in this framework. In addition, we compare the performance of our baseline Quantile Regression with a SSVS prior for $\tau = 0.5$.

Model estimation is performed recursively, keeping the first 117 quarters (roughly halve of the sample) as a training sample. The forecasting exercise proceeds through time by updating the training sample and re-estimating the model. The relative RMSFE are computed for three sub-samples 1978-1985, 1986-1999 and 2000-2009 and three projection horizons $h = \{1, 4, 8\}$ following Stock and Watson (2003).

The performance of the various individual systemic risk indicators relative to the autoregressive benchmark can be assessed by analysing the relative RMSFE. Values of less than one suggests that the specific Systemic Risk indicator adds value to GDP growth forecasts as compared to the AR(2) model. The first two rows report the RMSFE of the pseudo out-of-sample forecasts for the AR(2) and the quantile regression for the 50th percentile (corresponding to the median) in the three sub-samples considered. From the third row onwards relative RMSFE are reported. These should be interpreted as the improvement/deterioration of the forecast of GDP growth, relative to the random walk benchmark. A systemic risk indicator is considered to have relevant information content in predicting output growth if the relative MSFE is lower than 1. On the contrary, if a given measures has relative MSFE values greater or equal to 1, we conclude that it does not improve forecasting performance as it fails to outperform the random walk benchmark.

Table 4: Out-of-Sample MSFE of systemic risk indicators in predicting GDP growth, h-steps ahead.

#	Systemic risk indicator	1978-1985			1986-1999			2000-2009		
		horizon			horizon			horizon		
		h = 1	h = 4	h = 8	h = 1	h = 4	h = 8	h = 1	h = 4	h = 8
		RMSFE								
	baseline AR(2)	5.15	4.79	5.09	2.49	3.23	3.51	3.09	3.22	3.19
	Quantile regression	4.05***	1.93***	1.76***	1.77**	1.83***	1.86***	3.04	1.54***	1.48***
		RMSFE relative to the AR(2)								
1	absorption	1.02	1.00	1.00	1.02	1.01	1.00	0.99	1.00	1.00
2	Delta Absortion	1.00	1.00	1.00	1.00	1.00	0.99**	1.00	1.00	1.00
3	AIM	1.07	1.02	1.00	1.01	1.01	1.00	0.95***	1.00	1.00
4	CatFin	0.99	1.01	1.00	1.20	1.08	1.03	1.18	1.08	1.03
5	GZ spread	0.97	1.01	1.01	1.10	1.02	1.01	0.94	1.00	1.01
6	Baa/Aaa Bond yield	0.99**	0.99*	1.00	0.98	0.98**	0.99**	0.96	1.00	1.00
7	TED spread	-	-	1.20	1.02	1.01	1.00	0.93*	1.00	1.00
8	Term Spread	0.99	0.99	1.00	0.99	0.97**	0.99**	0.99	0.97***	0.98***
9	Baa/10-yr T-rate spread	1.02	1.01	1.00	1.00	0.99**	0.99***	1.00	0.99*	0.99**
10	Mortg-GS10 Spread	1.05	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00
11	Comm. paper-3mT-Bill spread	0.97	1.01	1.00	0.98	1.02	1.01	0.89***	0.97**	1.00
12	Excess Bond Premium	1.02	1.01	1.00	1.00	1.00	1.00	1.03	1.03	1.01
13	Intl. Spillover	1.01	1.00	1.00	1.00	1.00	1.00	0.98	1.01	1.00
14	CoVaR	0.99**	0.99**	1.00	1.12	1.04	1.01	1.06	1.01	1.00
15	Delta CoVaR	0.99**	1.00	1.00	1.07	1.02	1.01	1.04	1.01	1.00
16	Book lvg.	1.02	0.99	1.00	1.02	1.01	1.00	1.00	1.00	1.00
17	Mkt. Lvg.	1.00	0.99	1.00	1.01	1.00	1.00	1.02	1.00	1.01
18	DCI	0.96*	1.00	1.00	1.11	1.02	1.00	1.01	1.01	1.00
19	MES	0.99*	1.00	1.00	1.07	1.02	1.01	1.00	1.00	1.00
20	MES-BE	1.00	1.00	1.00	0.95**	0.95***	0.98***	1.05	0.99	1.00
21	Volatility	1.01	1.01	1.01	1.30	1.13	1.05	1.21	1.07	1.03
22	Size conc.	1.02	1.01	1.00	1.05	1.02	1.01	0.99***	0.99***	0.99*
23	Turbulence	1.01	1.00	1.00	1.03	1.02	1.01	0.97	1.02	1.01
24	PQR	0.98	1.00	1.00	0.94**	0.98**	0.99**	1.00	0.99	1.00
25	Average DD.	-	-	-	-	-	-	2.66	1.36	0.76 †
26	portfolio DD.	-	-	-	-	-	-	2.73	1.40	0.77 †
27	MRI CITI Index	-	-	-	1.17	1.08	0.80	1.05	1.01	1.00
28	CAPE	0.96**	0.98	1.00	0.94	0.99	1.00	1.07	1.05	1.02
29	VXO	1.00	1.01	1.00	1.13	1.06	1.02	1.06	1.04	1.02
30	Sent. Index	1.01	1.01	1.00	1.02	1.01	1.01	1.00	1.00	1.00
31	Credit-to-gdp gap	1.00	1.00	1.00	1.09	1.03	1.01	1.04	1.02	1.01
32	Debt Service Ratio	-	-	-	1.23	0.08	0.11	1.12	1.00	1.01
33	Loan Supply	-	-	-	1.02	1.02	1.07	1.03	1.02	1.01

Notes: Summary of pseudo out-of-sample forecast accuracy for three periods (1978-85, 1985-2000 and 2000-09) and three forecast horizons ($h = \{1, 4, 8\}$ quarters). Entries for each systemic risk indicator refer to the relative Root Mean Square Forecast Error (RMSFE) for recursive, out-of-sample forecasts constructed by augmenting an AR(2) with the respective systemic risk indicator, relative to the AR(2) benchmark. The quantile regression is estimated with the SSVS prior and included two lags, an intercept and the CFNAI, which is not reported. The Diebold-Mariano statistic reported refers to the test for equal predictive accurary relative to the AR(2) and makes use of the finite sample adjustment of Harvey et al. (1997) and Newey-West standard errors. Starts next to the relative RMSFE indicate the point (density) forecast performance is significantly better than the AR(2) at 1 %(***), 5 %(**) and 10 %(*).The † highlights points for which the observations of forecast errors is too short to calculate DM statistics.

Inspection of Table 4 reveals that few systemic risk indicators forecasts beat the random walk benchmark in some subsamples. For example, the GDP growth forecast 4 and 8 quarters ahead based on the term spread and Moody's Seasoned Baa Corporate Bond Yield have relative RMSFE lower than one. Overall however, very few systemic risk indicators improve forecasting performance of GDP growth and improvements in forecasting ability are infrequent and isolated.

6 Conclusion

In this paper we study 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 practical utility of these indicators in improving economic growth forecasting. To deal with a large number of possible predictors, we employ sparse-modelling techniques to perform variable selection and shrinkage. These include a Stochastic Search and Variable Selection and 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 a subset of systemic risk indicators are relevant in describing the interaction between systemic risk and output. Understanding which particular indicator merits inclusion in the regression to explain lower tails of the growth distribution, which we call 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. In this regard, we specify a SSVS prior that is used to derive the main results and analyse the sensitivity of the findings by using alternative methods of imposing sparsity in the model.

In-sample analysis suggests that a subset systemic risk measures contain relevant information that explain future developments of GDP growth. However, less than halve of the systemic risk indicators considered are selected as relevant predictors of lower quantiles of GDP growth, suggesting that it is particularly hard to foresee economic downturns and that most systemic risk indicators contain limited recession-relevant information. In another domain, we analyse the extent to which results change when we re-estimate the model using a rolling window of data covering the length of approximately three average business cycles. We find that even less systemic risk indicators forecast real activity at different periods of time. The term spread is the most relevant indicator in predicting future develops of GDP before the year 1996.

Out-of-sample analysis suggest systemic risk indicators improve economic growth forecasting occasionally but these pockets of predictability are rare and short-lasting.

Appendix A Data

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 3M and 10Yr 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.

Table 5: Data Description and Sources.

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

$$p(\lambda|y, z, \beta, \gamma, \delta^{-2}) \sim Gamma(\bar{c_0}, \bar{c_1}),$$
$$with \quad \bar{c_0} = r \quad and \quad \bar{c_1} = \sum_{j=1}^{p} \gamma_j/2 + \Delta.$$

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)). In particular, Giannone et al. (2017) highlights that the Ridge regression can be viewed as a particular case of the SSVS model. The authors highlight that the Ridge regression can be obtained by simply setting $\pi_0 = 1$. This alteration is effortless and does not require any change of the SSVS Gibbs Sampler described above. It is worth noting that, by setting $\pi_0 = 1$ the hierarchy described above boils down to a Normal-Inverse Gamma model (layers 4 and 5 are eliminated).

Appendix C Convergence Diagnostics

This subsection examines the convergence of the Markov Chain Monte Carlo in the baseline specification. Although convergence of univariates regressions is not very sensitive to either starting points of the chain or size of the burn-in period, high autocorrelation of the draws means inefficiency factors of β_τ can be quite high. Therefore we perform thinning whereby one in every 10 draws is saved. This is found to lower inefficiency factors to acceptable levels in line with those reported in Kozumi and Kobayashi (2011).

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

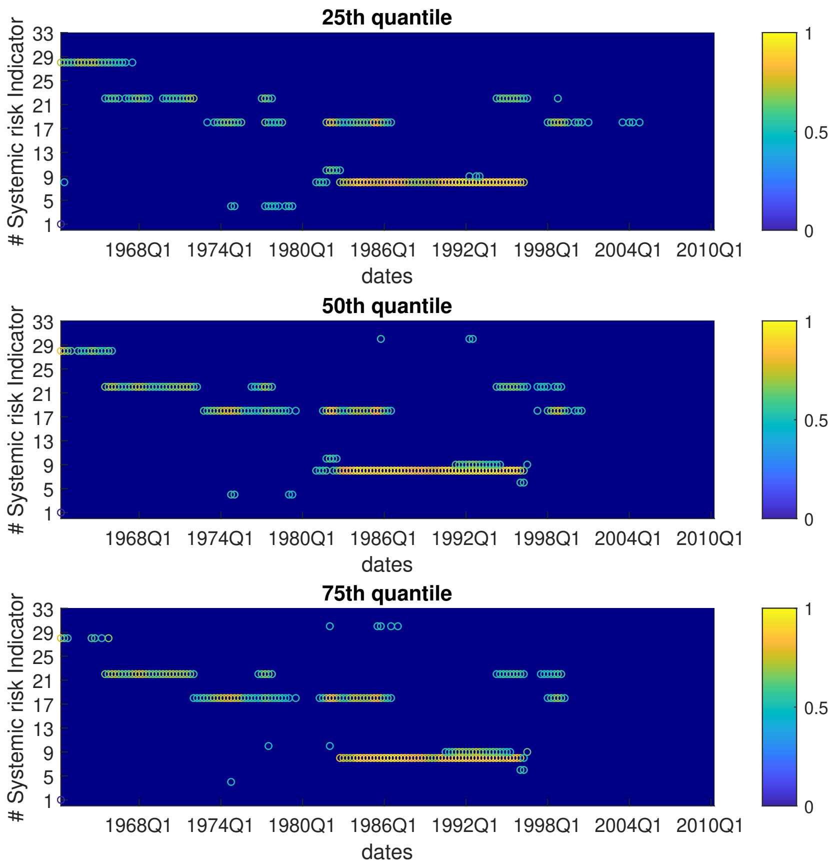
#	Systemic risk indicator	$\beta_{j,\tau=0.25}$	$\beta_{j,\tau=0.50}$	$\beta_{j,\tau=0.75}$
1	absorption	1.89	1.75	2.16
2	Delta Absortion	1.04	1.24	1.75
3	AIM	2.88	1.36	2.01
4	CatFin	1.06	1.47	0.92
5	GZ spread	2.33	1.55	1.46
6	Baa/Aaa Bond yield	2.86	2.35	2.67
7	TED spread	3.56	1.12	1.83
8	Term Spread	1.68	2.02	0.95
9	Baa/10-yr T-rate spread	2.08	1.58	1.70
10	Mortg-GS10 Spread	5.83	5.17	2.40
11	Comm. paper-3mT-Bill spread	2.12	4.00	5.27
12	Excess Bond Premium	2.29	1.66	1.48
13	Intl. Spillover	1.91	1.22	1.91
14	CoVaR	6.62	2.91	3.10
15	Delta CoVaR	7.41	5.41	3.79
16	Book lvg.	2.78	2.05	2.63
17	Mkt. Lvg.	2.21	1.92	1.46
18	DCI	0.67	0.85	1.35
19	MES	3.67	2.15	2.14
20	MES-BE	0.89	1.02	0.51
21	Volatility	0.59	1.29	0.87
22	Size conc.	3.03	1.19	1.02
23	Turbulence	1.61	1.44	1.40
24	PQR	0.77	1.04	1.39
25	Average DD.	0.81	0.62	1.64
26	portfolio DD.	0.81	0.53	1.19
27	MRI CITI Index	0.84	1.16	0.74
28	CAPE	3.85	3.98	2.43
29	VXO	3.74	8.94	5.26
30	Sent. Index	3.13	1.99	2.65
31	Credit-to-gdp gap	4.25	3.75	3.88
32	Debt Service Ratio	3.45	4.78	2.86
33	Loan Supply	1.23	1.86	1.10

Notes: The inefficiency factors are calculated for a MCMC run of 13000 draws and 3000 burn-ins. Thinning is performed whereby a single draw out of every 10 is saved for inference.

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. In our exercise, average inefficiency factors are approximately 5. Increasing the number of draws could perhaps lower further inefficiency factors. However, we find that the computational burden necessary to lower significantly inefficiency factors further to be prohibitive.

Appendix D Additional Tables & Figures

Figure 3: Systemic risk indicators automatically selected as predictors of the lower, middle and upper percentiles of GDP, 1 year ahead and respective probabilities of inclusion. Colour of the rings depict the probability of inclusion of each indicator, for each period.



Notes: The dots in the heat-map refer to the indicators for which the average probability of inclusion (ie, the posterior mean of γ_p across intervals of p) is greater than 0.5 and therefore selected on a rolling window of 59 quarters, one-year ahead. The colour of the rings depict the average probability of inclusion of each indicator, for each period. The regression includes 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.

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