Time Varying Disaster Risk*

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Abstract. We propose in this article a simple measure - called the Macroeconomic Value-at-Risk (MVaR), to quantify disaster risk, i.e. the risk of very large but infrequent recessions such as the Great Depression and the Great Recession. Based on quantile regressions, we find that the Value-at-Risk of macroeconomic fluctuations evolves over time. We build several financial stress and systemic risk measures spanning nearly four decades. Empirically, we show that financial stress measures provide significant predictive information for the lower tail of future macroeconomic fluctuations. Systemic risk leads disaster risk.

JEL Classification: C21, C53, E32, E44, G2.

1. Introduction

The phenomenon of fat tail distribution is commonly observed in financial returns data. In assessing risks, the focus of analysis is on low probability events with a high potential for devastating consequences when they occur. Risk managers and regulators turn to the concept of Value-at-Risk (denoted VaR hereafter), which is a measure of the worst potential loss over a specific time horizon, at a given probability[1].

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[1] The VaR has been widely accepted in financial markets since the mid-nineties. It was first popularized by JP Morgan and later by the RiskMetrics Group in their risk management software. VaR then was approved by bank regulators as a valid approach for calculating risk charges. But there are two well-known limitations of VaR measures: (a) they do not take into account the size of tail losses and (b) they lack "coherence" in the sense of Artzner et al. (1999), since they do not satisfy the sub-additivity property required for consistent risk ordering. This means that VaR may be incapable of identifying diversification opportunities. Although there has been a good deal of criticism of VaR in the literature because of these shortcomings, it remains a widely used method for risk measurement by practitioners, mainly because it has an intuitive interpretation, can be easily back-tested, and is required by regulation. More-

In this article, we measure the tail risk in macroeconomic fluctuations. We estimate the risk of economic disasters, i.e. large but infrequent drops in economic activity. To quantify this disaster risk, we propose a simple measure, called Macroeconomic Value-at-Risk (MVaR), which is precisely defined as the Value-at-Risk of macroeconomic fluctuations. Sparked by the recent "Great Recession" and the role of financial markets, many systemic risk measures have been proposed. We assess, using quantile regressions, if systemic risk measures are informative about future economic disasters.

Figure 1 illustrates the main objective of the paper: forecast low quantiles of macroeconomic fluctuations using financial stress indicators. This Figure represents the Chicago Fed National Activity Index from 1973M3 to 2014M7 (by dots) and the in-sample forecast of the CFNAI VaR95% (the line). The forecasting model only includes a constant and an individual financial stress variable, namely the default spread (the difference between yields on BAA and AAA corporate bonds).

[Insert Fig.1]

To give a simple intuition of the usefulness of the quantile regression approach in our context, we may consider an analysis of a simple forecasting model for the CFNAI. Figure 2 represents the scatterplot of the monthly CFNAI against the lagged default spread over the period 1975M3:2014M7, as well as the fitted conditional quantile lines for a range of quantiles between the 5th to the 50th percentile. This Figure show the conditional distribution of macroeconomic fluctuations at date t+1 at any given level of systemic risk observed at date *t*. The slope of this relationship depends on the predicted quantile, with a forecasting model that appear to be non-linear. Financial distress leads to a higher macroeconomic tail risk.

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over, recent literature provides some evidence that sub-additivity might not be such a severe issue (see Daníelsson et al., 2013).

[Insert Fig.2]

Within theoretical asset pricing, the importance of rare consumption disasters originated with Rietz (1988) as a solution to the equity *premium* puzzle. Barro (2006) revives this formulation by extending the Rietz (1988) model and calibrating the magnitude and probability of economic disasters to match historical international data. Gabaix (2012) augments the Barro-Rietz framework to accommodate the time-varying intensity of disasters and provides closed-form solutions to a number of asset pricing puzzles. Wachter (2013) offers a continuous-time model with a time-varying probability of a consumption disaster in an economy with recursive preferences and unit intertemporal elasticity. Gourio (2013) builds a real business cycle model with rare disasters to explore the interaction between business cycles and disasters. In all of these models, assets with a positive payoff during times of high disaster risk, command a lower equity *premium* over a risk-free asset.

The conduct of monetary policy has been recently associated with a risk management practice both in monetary policy statements (Greenspan, 2003 and Mishkin, 2008) and in academic research (Kilian and Manganelli, 2008). This risk management perspective of monetary policy is directly inspired by the literature on robust control (Hansen and Sargent, 2003, 2007). The key idea of robust control is that policy-making should aim at minimizing the consequences of worst-case scenarii.

The idea that the financial sector can amplify the business cycle dates back to at least Fisher (1933). Traditionally, financial shocks were transmitted through the channel of the cost of credit (or the interest rate channel) and wealth effects (Cf., e.g., Lettau and Ludvigson, 2004). Since the works developed by Bernanke and Blinder (1988) and Bernanke and Gertler (1995, 1996), it is agreed that financial imperfections resulting from information asymmetries contribute to the transmission and the amplification of monetary and credit shocks. More recently, studies have shown that the analytical framework of the financial accelerator could be extended to other agents such as non-financial intermediaries. This new financial accelerator describes how the financial system amplifies the impact on the real economy.

The financial accelerator mechanism has been clearly illustrated by Adrian and Shin (2008) where a negative shock to asset prices depletes bank capital, causing leverage to increase. Since it is difficult to raise new capital in times of crisis, banks tend to liquidate their assets. These disposals, as fire sales, accentuate the drop in asset prices and finally amplify the initial shock. The multiplication factor derives from banks' leverage and can lead to massive asset liquidation, thus triggering a vicious circle, particularly if banks want to restore target leverage or debt ratio (or a capital adequacy ratio imposed by regulators). This feedback loop mechanism can in turn have a strong impact on economic activity, especially in the case of systemic events. In trying to restore their capital ratio, *i.e.* to reduce their leverage, the risk is that banks will also scale down loans to the non-financial sector. This so-called risk of a credit crunch was indeed one of the main concerns raised following the 2007-2008 financial crisis.

It follows that, with disaster risk being in the tail of the macroeconomic fluctuations, standard time-series macroeconometric models focusing on estimating the mean are not well suited to empirically implementing a risk-management approach. Methods based on the logic of ordinary least squares regression or maximum likelihood estimation do provide information about shifts or translations in the distribution of possible outcomes. However, policy makers, while interested in these shifts or translations, are also concerned about whether the evolution of exogenous conditions has had an impact on the shape of the output distribution.

That is why we herein dynamically estimate, using quantile regressions, the probability distribution of future outputs, as opposed to simple mean and/or variance point estimates. Since at least Engle (1982) and Stock and Watson (2002), we know that the conditional variance of future output and inflation evolves over time. However, in these seminal contributions the risk of macroeconomic fluctuation is implicitly considered symmetric. Our framework, model-based and judgement-free, allows the shape of the output distribution to be measured conditionally on the current state of the economy.

Quantile regression (Koenker and Basset, 1978 and Koenker, 2005) can be considered as a natural extension of the classical least squares estimation of conditional mean models to the estimation of a set of models for conditional quantile functions. The central special case is the median regression estimator that minimizes a sum of absolute errors. The remaining conditional quantile functions are estimated by minimizing an asymmetrically weighted sum of absolute errors. Altogether, the set of estimated conditional quantile functions offers a much more complete view of the effect of covariates on the location, scale and shape of the distribution of the response variable.

Recently, given that a significant financial stress triggers severe macroeconomic downturns, researchers and policy makers have considered systemic risk as an acute issue. Numerous systemic risk measures were thus proposed after the 2007-2009 financial crisis.[2] Nevertheless, as mentioned by several authors, one could however regret the lack of an objective criterion for gauging the information content of such measures, as well as comprehensive studies of their fragility/robustness and final usefulness – e.g., Bernard et al. (2012), López-Espinoza et al. (2012), Hansen (2013), Hurlin et al. (2013), Hurlin et Pérignon (2013), Idier et al. (2013), Lo Duca and Peltonen (2013), Peña and Rodríguez-Moreno (2013), Girardi and Ergün (2013), Daníels-

[2] See Bisias et al. (2012) for an extensive survey and www.systemic-risk-hub.org for complementary references.

son et al. (2014), Döring et al. (2014), Giglio et al. (2014), and Tavolaro and Visnovsky (2014).

Moreover, Giglio et al. (2014) highlight the fact that one important *criterion* of their over-all efficiency might be in the fact that systemic risk measures indeed should truly be linked – somehow – to major macroeconomic downturns. In other words, since we hypothetically have in mind a strong link between global financial stresses and economic recessions *via* the accelerator mechanism, we can assume that a well-built informative systemic risk measure should provide leading information on macro-economic shocks.

As in Giglio et al. (2014), our estimates of conditional macroeconomic quantiles thus permit us to measure how the distribution of future macroeconomic variables responds to systemic risk/financial stress factors. The ability to predict very low quantiles of macroeconomics fluctuations should also serve as a realistic empirical *criterion* when evaluating these systemic risk measures; in other words, we can think that an important systemic risk – when accurately quantified by a sound systemic risk measure, should have consequences in terms of output consequences. However, Giglio et al. (2014) mainly focus on the 20th percentile, while our interest is hereafter principally in lower quantile characterizing severe crises, such as the 5^{th} percentile, since our objective is to establish some links between systemic risk measures and economic disaster risk and rare events.

The rest of the paper is organized as follows. In Section 2, we present the empirical framework. In particular, Section 2.1 briefly introduces the quantile regression methodology. Section 2.2 presents the data and Section 2.3 discusses some preliminary analyses based on a simple VaR methodology. Section 3 is a discussion about the empirical results from quantile regressions. Section 4 summarizes our conclusions.

2. On the extreme risk of economic activity: the empirical framework

In the following, we briefly describe in a very general way the quantile regression approach and the main underlying intuition, as well as the data. For a more technical presentation on financial data, see, *e.g.* Engle and Manganelli (2004).

2.1 CONDITIONAL ACTIVITY RESPONSE TO SHOCK WITH QUANTILE REGRESSIONS

In order to address how changes in a set of conditioning variables influence the shape of the distribution of a dependent variable, Koenker and Bassett (1978) developed the concept of "quantile regressions". Quantile regressions are designed to answer the following question: when a conditioning variable x changes, what happens to the τ *-th* quantile of the distribution of a linked variable y ?

Quantile regression can better quantify the conditional distribution of $(y \mid x)$. The estimates of conditional quantile functions are obtained by minimizing an asymmetrically weighted sum of absolute errors, where the weights are the function of the quantile of interest. Taken together, the set of estimated conditional quantile functions of $(y \mid x)$ offers a more complete view of the effect of covariates on the location, scale and shape of the distribution of the response variable. In the classical approach of OLS regression, the conditional mean function that describes how the mean of y changes with the vector of covariates x is (almost) all we need to know about the relationship between y and x. Classical OLS is considered a pure location shift model since it assumes that x affects only the location of the conditional distribution of y, not its scale, nor any other aspect of its distributional shape.

Covariates may influence the conditional distribution of the response in a myriad of other ways: expanding its dispersion as in traditional models of heteroskedasticity, stretching one tail of the distribution, compressing the other tail, and even inducing multi-modality. An explicit investigation of these effects *via* quantile regression can provide a more precise view of the stochastic relationship between variables, and therefore a more informative empirical analysis.

Parameter estimation in quantile regression is the result of an optimization problem. Recall that one can write down an OLS solution as an optimization problem where one minimizes the sum of squared deviations of the fitted values for the dependent variable from the data. In the same way, the median quantile (.50) in quantile regressions is defined as the problem of minimizing the sum of absolute residuals. The symmetrical piecewise linear absolute value function ensures the equal number of observations above and below the median of the distribution.

The other quantile values can be obtained by minimizing a sum of asymmetrically weighted absolute residuals, thereby giving different weights to positive and negative residuals. Thus, solving:

$$Arg\left\{\min_{\xi\in\mathbf{R}}\left[\sum_{i=1}^{n}\rho_{\tau}\left(y_i-\xi\right)\right]\right\}, \quad (1)$$

where $\rho_{\tau}(\cdot)$ is the tilted absolute value function (usually called “pinball loss function”), giving the τ *-th* sample quantile with its solution as illustrated in Figure 3. Depending on the exact shape of the function $\rho_{\tau}(\cdot)$, the optimization problem yields an estimate at a particular quantile. This quantile depends on the relative slopes on the two sides of the origin.

[Insert Fig. 3]

The sample quantile becomes the solution to this problem when we take the directional derivatives of the objective function with respect to ξ (from left to right).

After defining the unconditional quantiles as solutions to an optimization problem, it is easy to similarly define conditional quantiles. Taking the least squares regression model for a random sample, $[y_1, y_2, ..., y_n]$, we solve:

$$Arg\left\{\min_{\mu\in\mathbf{R}}\left[\sum_{i=1}^{n}(y_i-\mu)^2\right]\right\}, \tag{2}$$

which gives the sample mean, an estimate of the unconditional population mean. Replacing the scalar, μ, by a parametric *p*-dimensional function $\mu(x,\beta)$, with β a set of parameter sensitivities, and then solving:

$$Arg\left\{\min_{\mu\in\mathbf{R^P}}\left\{\sum_{i=1}^{n}\left[y_i-\mu(x_i,\beta)\right]^2\right\}\right\} \tag{3}$$

gives an estimate of the conditional expectation function $E(y\,|\,x)$.

Proceeding the same way for quantile regression, in order to obtain an estimate of the conditional median function, the scalar ξ in the first equation is replaced by the parametric function $\xi(x,\beta)$, and τ is set to .5. Finally, the estimation of the 99-*th* percentile line in addition to the standard “mean” line, makes possible the production of not only a mean forecast, but also a distribution of forecasts around this mean.

Quantile regressions have already been applied in a variety of economic and financial problems. Applications include investigations of wage structure (Buchinsky and Leslie, 2010), wage mobility (Buchinsky and Hunt, 1996), and educational attainment (Eide and Showalter, 1998). Financial applications include problems of robust beta estimation (Chan and Lakonishok, 1992) and financial return Value-at-Risk forecasts (Engle and Manganelli, 2004).

2.2 ECONOMIC ACTIVITY EXPLANATORY VARIABLES AND DATABASES

We consider US macroeconomic fluctuations measured by the Chicago Fed National Activity Index (CFNAI). It is a broad measure of monthly real economic activity in the US, obtained from applying principal component analysis on 85 existing monthly indicators of real activity. Theses economic indicators included in the CFNAI are drawn from 4 broad categories of data: production and income; employment, unemployment and hours; personal consumption and housing; sales, orders and inventories. Each of these data series measures some aspect of overall macroeconomic activity. The derived index provides a single, summary measure of a factor common to these national economic data. This index corresponds to the economic activity index developed by Stock and Watson (1999).

Quantile regressions presented hereafter are implemented using US monthly time series for the period from March 1975 to July 2014. All series come from the FRED II Database of the Federal Reserve Bank of St-Louis, Datastream and Bloomberg. The sample is constrained by the availability of the house price index.

Our objective is to forecast the low quantiles of real activity growth (5%), what we call MVaR, and investigate the relative and absolute forecasting power of systemic risk measures.

We consider five individual and 3 aggregate systemic risk measures: a bank's credit and liquidity spread (the Ted spread[3] denoted TED_t), a default or credit spread (defined as the yield difference between Moody's BAA and AAA corporate bonds denoted DEF_t), the implied volatility of the S&P equity index (VIX_t), the CoVaR

[3]The TED spread is the difference between the interest rate on three months' uncollateralized interbank LIBOR loans and the interest rates on Treasury bills. In times of uncertainty, banks charge higher interest for unsecured loans, which increases the LIBOR rate. Furthermore, banks want to get first-rate collateral, which makes holding Treasury bonds more attractive and pushes down the Treasury bond rate.

from Adrian and Brunnermeier (2011), denoted $CoVaR_t$, the MES (for marginal expected shortfall, denoted MES_t) from Acharya et al. (2010) and three aggregate indicators of financial stress calculated respectively by the Federal Reserve Bank of Kansas City (KCFSI), the Federal Reserve Bank of Cleveland (CFSI), the Federal Reserve Bank of St Louis (STLFSI), respectively denoted as $Stress1_t$, $Stress2_t$ and $Stress3_t$ [4].

The CoVaR is defined as the VaR of the financial system as a whole conditional on an institution being in distress. The distress of the institution, in turn, is captured by the institution being at its own individual VaR (at quantile 5% in our case).

The MES captures the exposure of each individual firm to shocks to the aggregate system, i.e. the expected return of a firm conditional on the system being in its lower tail (quantile 5% here). For these two measures, we use a 252 days rolling window and the Datastream equity index of the banking sector for the returns of institutions and the return of the S&P500 index for the aggregate system. Monthly data used in the quantile regressions are end-of-month values of these two daily systemic risk measures.

Building on eleven daily financial market indicators as input series, Hakkio and Keeton (2009) at the Federal Reserve Bank of Kansas City construct a monthly FSI (the "KCFSI") applying principal components analysis to US data. The idea is that financial stress is the factor most responsible for the observed correlation between the indicators, and this factor is identified by the first principal component (the first eigenvalue) of the sample correlation matrix computed for the standardised indicators. The weights with which each individual indicator enters into the KCFSI are computed from the indicators' loadings to the first principal component, i.e. from the first eigenvector of the correlation matrix. Applying the same methodology, Kliesen and Smith

[4] See the web appendix (available from the authors) for some details about data reconstruction for some variables.

(2010) aggregate 18 weekly financial market indicators into the "St. Louis Fed's Financial Stress Index" (STLFSI).

The "Cleveland Financial Stress Index" (CFSI) developed by Oet et al. (2011) integrates 11 daily financial market indicators which are grouped into four sectors (debt, equity, foreign exchange and banking markets). The raw indicators are normalised by transforming the values of each series into the corresponding value of their empirical cumulative density function. The aggregation of the components is implemented using a credit weighting scheme. The four sectors are weighted according to quarterly data on their share of total credit, including debt, equity, foreign exchange, and banking markets.

Globally, these stress measures aim to identify the main factors that summarize co-movements of the various individual distress measures with some different weighting schemes.

Figure 4 plots the monthly time series of the z-score of the individual and aggregate systemic risk measures from 1975M3 to 2014M7. To facilitate comparisons we represent the z-scores of the marginal expected shortfall and the *CoVaR* multiplied by the factor (-1) (i.e. - *MES* and - *CoVaR* respectively). Not surprisingly, all measures spiked during the recent global financial crisis. However, for some measures the highest peak is not observed in 2008 but at the beginning of the 1980s (*TED* and *Stress2*) during the great inflation and the aftermath of the oil crises. Some measures jumped at the beginning of the 1980s and/or the end of 1970s with the exception of the *CoVaR* and the *MES*. Some measures display substantial variability such as the *VIX* or the *Stress2* even in non-recessionary periods but, globally; financial stress measures occasionally experience high levels or jumps.

[Insert Fig.4]

In addition to these systemic risk measures, we include three control variables when forecasting the MVAR95%. We consider the slope of the yield curve or term spread (the difference between the 10-year Treasury bond yield and the 3-month Treasury bond yield), $TERM_t$. The second control variable is the real oil price growth, OIL_t [5]. And finally, we introduce the real house price growth rate, HP_t [6].

The relationship between economic activity and the term structure of interest rates has been widely studied in the last decades. A large number of studies has concentrated on the predictive power of the difference between long and short yields (the term spread or yield curve slope) regarding future GDP growth (e.g. Harvey, 1988). Others have verified whether the term spread informs about the probabilities of future recessions (e.g. Estrella and Mishkin, 1998; Wright, 2006). The rationale behind the predictive ability of the term spread rests mainly on the forward looking behaviour of market participants that anticipate future reactions of the central bank (Ang et al., 2006).

There is also a long tradition of associating U.S. recessions with oil price shocks. Hamilton (2009) and Ramey and Vine (2011), stress the importance of oil price increases for the economic slowdowns. The key mechanism whereby energy price shocks affect the economy is through a disruption in consumers' and firms' spending on goods and services other than energy.

Finally, as an additional control variable, we also include the real house price growth rate (or return) due to the very special role of the housing market in the Great Recession and also since housing price busts in industrial countries coincide with sharp slowdowns in economic activity and with outright recessions (Helbing, 2005).

Table I presents the correlation matrix of the 8 financial stress measures, the CFNAI and our control variables (the real estate return, the slope of the yield curve

[5]The oil price index comes from Bloomberg (Cushing, OK WTI Spot Price FOB - Dollars per Barrel) and Hamilton (2009) before January 1981. The oil price index is then deflated using the Consumer Price Index.

[6]The house price index is built from the Case-Shiller index and the OFHEO index before January 1987 (with the Consumer Price Index to deflate the house price index).

and real oil price growth). First of all, the CFNAI has globally intermediate correlations levels with the financial stress measures (between 25% and 45% in absolute value). Globally, correlations between the control variables and the stress measures are low with the exception of the real estate return due to the typical scheme of the global financial crisis in 2007-2008. The real oil price growth has very low correlation coefficients with the financial stress variables. On the contrary, the aggregate systemic risk measures have relatively high correlations coefficients (between 70% and 90%). Indeed, the three aggregate systemic risk measures are based on many similar individual financial stress measures. For the individual financial distress variables, except for the *MES* and the *CoVaR* highly correlated, correlations are at intermediate levels (between 45% and 50%) in absolute values. However, even if correlation coefficients between aggregate systemic risk measures are relatively high, Figure 4 showed that the behavior of these measures could be quite different during bad times.

[Insert Tab.1]

Overall, the empirical comparison of systemic risk measures shows that the information they included is quite heterogeneous, with the exception of the *MES* and the *CoVaR*, since each measures captures different aspects of systemic risk. Hence, we need a criterion to compare these financial distress measures. We propose, in the next session, to investigate the forecasting power of the various systemic risk measures on the disaster risk, i.e. low quantiles of macroeconomic fluctuations[7].

[7] As a preliminary analysis we investigate causality and relationships between our set of macroeconomic and financial distress measures. A Vector AutoRegressive (VAR) model is estimated with 7 lags selected, based on the Akaïke Information Criterion. Simple Granger causality tests (available upon request) suggest that financial stress indicators and industrial production have a double causality at the 1% and 5% significance level.

3. Forecasting disaster risk with Systemic Risk measures

Table II reports the results of the multivariate forecasting 5% quantile regressions of CFNAI. Several multivariate regressions are herein examined based on the various systemic risk measures and three control variables over the period 1975M3-2014M7. All potential predictors are considered with a delay, since we are interested in forecasting the conditional distribution of the macroeconomic fluctuations. We consider multivariate models with/without an autoregressive term in Panel A and in Panel B respectively. These two specifications permit to evaluate if systemic risk measures have some information about future disaster risk (Panel B) and if this information is not ever included in the past realizations of the macroeconomic fluctuations. The coefficients and the t-stats are not shown for the constant, the autoregressive term and the control variables to save space (the rows for specifications #1 and#11 are thus empty except the two statistics about the forecasting performance). Student statistics (based on pair-bootstrapped standard errors) of the estimated coefficients are reported in parentheses in the tables and the last column presents two statistics to assess the relevance of the regressions carried out: the first one measures the frequency of Hits for the VaR estimated, and the second one, the sum of the absolute value of these Hits (shown in brackets). Hits are defined as exceedances of the estimated VaR.

[Insert Tab.2]

These results from Table II indicate that the introduction of some financial distress measures significantly impacts the MVaR at a 95% threshold (quantile at 5%). The size of errors decreases when considering models with some of the systemic risk measures. The Hit size in the specification #1, i.e. excluding financial distress measures, which only includes an autoregressive term, a constant and the three control variables is 9.54. The three specifications with respectively the two spreads, *TED* and *DEF*, and the aggregate measure *Stress1* have smaller Hits. All regression coefficients have the expected sign, i.e. positive for the *MES* and the *CoVaR* and negative for the remaining systemic risk measures. Only the *CoVaR*, the *MES* and the aggregate measure *Stress2* appear to be not statistically significant at a 95% confidence level when an autoregressive term is included (Panel A). All the financial distress measures become significant when we consider only one intercept and not anymore an autoregressive term (Panel B). Note that the specification #10 with both the Ted spread and the default spread presents the smaller Hits.

These in-sample results on the CFNAI show that some of the financial distress measures lead the future low quantiles of macroeconomic fluctuations since the coefficient are significant and the size of Hits is lower relative to multivariate models only based on the control variables.

Individual and aggregate systemic risk measures have a significant in-sample forecasting power on the low quantiles of real activity fluctuations. However, this effect could simply be the result of a displacement of the location or the central tendency of the conditional distribution. We investigate now how the relationship between the macroeconomic fluctuations and the lagged systemic risk measures evolves, depending on the predicted percentile. Figure 5 shows the slope of the predictive univariate regressions of the CFNAI on the various lagged financial stress measures, as well as the 95% confidence interval (based on pair-bootstrapped standard errors) for the various percentiles between 2.5% and 97.5%. Coefficients decrease with the percentiles for all the stress measures and decreases for the *CoVaR* and the *MES* (expressed as negative returns). These results show a non-linear relationship: a high lagged financial stress, such as high default spread or low *MES*, has relatively more (informational) impact on the lower tail of macroeconomic fluctuations. Financial intermediation stress has a significantly stronger elasticity with real activity in the lower tail of the distribution.

[Insert Fig.5]

To illustrate this non-linear pattern, we compare the predicted quantiles if two different states of nature: bad time and good times. Figure 6 presents various conditional quantiles from 2.5% to 50% of CFNAI in two different states of nature (quantiles estimated for March 2006 and October 2008) as well as their differences. We can conclude that financial stress impacts not only the location, but also the shape of the conditional distribution of activity.

[Insert Fig. 6]

Finally, we consider out-of-sample forecasts. Table III reports the two forecasting performance measures (the frequency and the size of Hits) obtained from out-of-sample forecasts using the period 1975M3-1990M1 for training, and recursively testing throughout the 1990-2014 sample to evaluate performance. All the models are univariate forecasting quantile regression models including a constant and a lagged financial distress measure. We also present the result of a simple model as a benchmark: forecasts based on the historical unconditional quantile.

All systemic risk measures perform better than the unconditional quantile in forecasting macroeconomic disasters. The frequency of Hits (CFNAI observations below the predicted MVAR95%) is much higher that the theoretical probability (5%) for the univariate quantile regression models with the aggregate financial distress measure *Stress3*, suggesting some instability in the predictive regressions.

Among the various systemic risk measures, the univariate model based on the default spread has the lower size of Hits. This due to a lower frequency of Hits (4% instead of the expected 5%), but also to a moderate average Hit size, since the model with the *MES* has a lower frequency of Hits but higher Hit size.

[Insert Tab.3]

4. Robustness checks

We assess the robustness of our main results in fours directions: the measure of macroeconomic fluctuations, a long historical evidence and the forecasting horizon.

First, Table IV and V reproduce Table II about the MVaR with two different measures of real activity fluctuations: the 5^{th} percentile of the industrial production growth and the 5^{th} percentile of the labor market conditions (the unemployment rate multiplied by the factor (-1)).

[Insert Tab.IV]

[Insert Tab.V]

Tables IV and V confirm, globally, that financial distress measures have a significant predictive power for economic disaster. All the measures are significant in the multivariate quantile regressions when forecasting the 5th percentile of the industrial production growth and the 5th percentile of the labor market conditions. Systemic risk measures are specifically informative when forecasting the downside distribution of real activity and upside distribution of the unemployment rate.

We also investigate the in-sample forecasting power of financial distress on economic disaster on a very long sample covering nearly one century: 1919M1-2014M7. Table VI presents the results of the univariate predictive quantile regressions of the MVAR95% of industrial production growth based on the default spread. The model includes a constant and an autoregressive term. We present for this long sample as well as for various sub-samples the coefficients, the bootstrapped t-stats, the frequency of Hits and the size of Hits.

[Insert Tab.VI]

The default spread has a significant predictive power on the various long samples. However, the forecasting performance measured by the size of the Hits as well as the coefficients appear unstable. While results appears relatively stable over the 1975M1-2014M7 period, as the previous out-of-sample results testified, over the longer samples the forecasting quantile regressions suffer from a lack of stability. This instability is probably the result of the evolution of the relationships between financial intermediation and the real economy as well as the nature of real activity with a rise of services over the period. Whatever, the default spread contains useful information, over nearly one century, about the future economic disasters.

Finally, we examine the nature of the lead-lag relationship between systemic risk measures and the future MVaR. Indeed, the min results presented are based on one lag predictors. We estimate univariate forecasting quantile regression models for the

CFNAI 5th percentile based on the various systemic risk measures considering various lags. For each predictor we estimate the forecasting quantile regression with one month to 12 months lag. Figure 7 presents the absolute values of the bootstrapped t-stats for each potential predictor, i.e. systemic risk measures, and the various lags. With the exception of the *TED* spread, the relevant information about the future tail risk of macroeconomic fluctuations appears mainly in the one lag specifications.

[Insert Fig.7]

5. Conclusion

We apply quantile regressions to estimate VaR of macroeconomic fluctuations (called MVaR). Our objective is to dynamically gauge the tail risk of real activity. Our results, based on monthly data from the US over the period of 1975M3-2014M7, suggest that not only the location and dispersion of the real activity evolve over time, but also the shape of the entire distribution. Financial intermediation stress has a significantly stronger elasticity with real activity in the lower tail of the distribution.

Interestingly, among the financial intermediation stress indicators, the default spread appears to summarize most of the relevant information about the tail risk of macroeconomic fluctuations. Indeed, credit markets have an important allocative role: for many large corporations, the bond market, much more than the equity market, is the “marginal source of finance”. The corporate bond market is of interest both because of its absolute size (around 5 trillion dollars, or one-third of GDP, in the US as of 2012) and because, while many firms do not access the corporate bond market directly and instead rely on bank loans, many of these loans are securitized and trade on a market similar to that of corporate bonds (Gourio, 2013).

Hence, we may conclude from this analysis that financial frictions lead to systemic risk eruption and then to higher economic disaster risks, *i.e.* a higher probability of severe recession.

These results strongly corroborate that monetary policy makers should not neglect financial intermediation disruptions in a risk management framework, since such disruptions can be responsible for, or at least be early warning indicators of, macroeconomic tail risks. Indeed, following the 2007/08 global financial crisis, debates about financial stability have emerged as a potential additional objective for Central Banks.

Our results were obtained using data from the US, where finance is more market based than bank based. These tests should be extended to other countries, for instance those of the Eurozone where finance is more bank-based.

Moreover, we propose to use our framework as a criterion to gauge the relevance of the systemic risk measures proposed in the future.

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Table I. Correlation Matrix

Notes: This table reports the correlation coefficients between the CFNAI, the control predictors and the systemic risk measures. Systemic risk measures considered are respectively (from left to right): the Ted Spread (difference between the interest rate on three months' uncollateralized interbank LIBOR loans and the interest rates on Treasury bills), the default spread (yield difference between Moody's BAA and AAA corporate bonds), the VIX (implied volatility of the S&P equity index), the CoVaR, the marginal expected shortfall, the Financial Stress Index of the Federal Reserve Bank of Kansas City (KCFSI), the Financial Stress Index of the Federal Reserve Bank of Cleveland (CFSI) and the Financial Stress Index of the Federal Reserve Bank of St Louis (STLFSI). Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2014M07. Computations by the authors.

	$CFNAI_t$	$TERM_t$	HP_t	OIL_t	TED_t	DEF_t	VIX_t	$CoVaR_t$	MES_t	$Stress1_t$	$Stress2_t$	$Stress3_t$
$CFNAI_t$	1	.03	.32	.08	-.26	-.45	-.25	.41	.42	-.38	-.30	-.43
$TERM_t$	.03	1	-.15	-.07	-.38	.12	.02	-.22	-.22	-.13	-.12	-.03
HP_t	.32	-.15	1	.05	-.05	-.20	-.09	.37	.38	-.07	-.01	-.17
OIL_t	.08	-.07	.05	1	-.02	-.10	-.10	.00	.02	-.10	-.04	-.15
TED_t	-.26	-.38	-.05	-.02	1	.50	.17	.19	.18	.76	.71	.62
DEF_t	-.45	.12	-.20	-.10	.50	1	.42	-.28	-.29	.85	.78	.74
VIX_t	-.25	.02	-.09	-.10	.17	.42	1	-.43	-.45	.49	.40	.59
$CoVaR_t$	.41	-.22	.37	.00	.19	-.28	-.43	1	1.00	-.13	-.07	-.25
MES_t	.42	-.22	.38	.02	.18	-.29	-.45	1.00	1	-.14	-.08	-.28
$Stress1_t$	-.38	-.13	-.07	-.10	.76	.85	.49	-.13	-.14	1	.90	.88
$Stress2_t$	-.30	-.12	-.01	-.04	.71	.78	.40	-.07	-.08	.90	1	.70
$Stress3_t$	-.43	-.03	-.17	-.15	.62	.74	.59	-.25	-.28	.88	.70	1

Table II. Forecasting quantile regressions of CFNAI (MVaR95%)

Notes: This table reports main regression results for the VaR95% of the CFNAI. Statistically significant coefficients (at 5%) appear in bold. The coefficients and the t-stats for constant and the control variables do not appear (Panels A and B) as well as the autoregressive term (Panel A). Systemic risk measures considered are respectively (from left to right): the Ted Spread (difference between the interest rate on three months' uncollateralized interbank LIBOR loans and the interest rates on Treasury bills), the default spread (yield difference between Moody's BAA and AAA corporate bonds), the VIX (implied volatility of the S&P equity index), the CoVaR, the marginal expected shortfall, the Financial Stress Index of the Federal Reserve Bank of Kansas City (KCFSI), the Financial Stress Index of the Federal Reserve Bank of Cleveland (CFSI) and the Financial Stress Index of the Federal Reserve Bank of St Louis (STLFSI). Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2014M07. Computations by the authors.

#	TED_t (t-stat)	DEF_t (t-stat)	VIX_t (t-stat)	$CoVaR_t$ (t-stat)	MES_t (t-stat)	$Stress1_t$ (t-stat)	$Stress2_t$ (t-stat)	$Stress3_t$ (t-stat)	Hit Freq. [Hit Size]
				Panel A: models with autoregressive term					
1									.042 [9.54]
2	**-.408** (-4.7)								.046 [7.87]
3		**-1.134** (-5.407)							.049 [7.985]
4			**-.038** (-3.898)						.048 [12.139]
5				7.851 (1.541)					.04 [9.602]
6					4.977 (1.24)				.042 [9.949]
7						**-.276** (-6.015)			.044 [8.152]
8							-.058 (-1.137)		.048 [11.2]
9								**-.288** (-4.298)	.044 [9.706]
10	**-.330** (-3.879)	**-.773** (-6.397)							.048 [7.591]
				Panel B: models without autoregressive term					
11									.042 [14.956]
12	**-1.005** (-7.579)								.048 [12.695]
13		**-1.282** (-7.502)							.044 [8.466]
14			**-.086** (-7.583)						.046 [13.954]
15				**27.365** (3.848)					.044 [12.077]
16					**21.174** (3.548)				.042 [11.924]
17						**-.498** (-9.458)			.042 [9.801]
18							**-.394** (-5.124)		.042 [11.67]
19								**-.704** (-9.921)	.04 [6.031]
20	-.182 (-1.414)	**-1.287** (-6.032)							.04 [6.658]

Table III. Out-of-sample forecasting VaR95% of CFNAI

Notes: This table reports main results of CFNAI 95% VaR out-of-sample forecasts. Two forecasting performance measures (the frequency and the size of Hits) are presented. We obtain from out-of-sample forecasts using the period 1975M3-1990M1 for training, and recursively testing throughout the 1990-2014 sample. All the models are univariate forecasting quantile regression models including a constant and a lagged financial distress measures. Systemic risk measures considered are respectively (from left to right): the Ted Spread (difference between the interest rate on three months' uncollateralized inter-bank LIBOR loans and the interest rates on Treasury bills), the default spread (yield difference between Moody's BAA and AAA corporate bonds), the VIX (implied volatility of the S&P equity index), the CoVaR, the marginal expected shortfall, the Financial Stress Index of the Federal Reserve Bank of Kansas City (KCFSI), the Financial Stress Index of the Federal Reserve Bank of Cleveland (CFSI) and the Financial Stress Index of the Federal Reserve Bank of St Louis (STLFSI). We also present the results of a simple model as a benchmark: forecasts based on the historical unconditional quantile. Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2014M07. Computations by the authors.

#	*uncondi-tional*	TED_t	DEF_t	VIX_t	$CoVaR_t$	MES_t	$Stress1_t$	$Stress2_t$	$Stress3_t$
Hit Freq.	.079	.058	.036	.058	.029	.029	.086	.101	.165
Hit Size	14.953	4.492	2.404	4.492	3.452	2.922	3.913	1.045	6.205

Table IV. Forecasting quantile regressions of the industrial production growth (MVaR95%)

Notes: This table reports main regression results for the VaR95% of the US industrial production growth. Statistically significant coefficients (at 5%) appear in bold. The coefficients and the t-stats for constant and the control variables do not appear (Panels A and B) as well as the autoregressive term (Panel A). Systemic risk measures considered are respectively (from left to right): the Ted Spread (difference between the interest rate on three months' uncollateralized interbank LIBOR loans and the interest rates on Treasury bills), the default spread (yield difference between Moody's BAA and AAA corporate bonds), the VIX (implied volatility of the S&P equity index), the CoVaR, the marginal expected shortfall, the Financial Stress Index of the Federal Reserve Bank of Kansas City (KCFSI), the Financial Stress Index of the Federal Reserve Bank of Cleveland (CFSI) and the Financial Stress Index of the Federal Reserve Bank of St Louis (STLFSI). Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2014M07. Computations by the authors.

#	TED_t (*t*-stat)	DEF_t (*t*-stat)	VIX_t (*t*-stat)	$CoVaR_t$ (*t*-stat)	MES_t (*t*-stat)	$Stress1_t$ (*t*-stat)	$Stress2_t$ (*t*-stat)	$Stress3_t$ (*t*-stat)	Hit Freq. [Hit Size]
Panel A: models with autoregressive term									
1									.039 [.1]
2	**-.003** (-4.49)								.042 [.085]
3		**-.007** (-6.371)							.042 [.088]
4			**-.000** (-3.85)						.042 [.111]
5				**.439** (7.591)					.06 [.133]
6					**.357** (9.062)				.058 [.148]
7						**-.002** (-5.063)			.044 [.084]
8							**-.002** (-4.548)		.095 [.24]
9								**-.004** (-4.659)	.104 [.258]
10	**-.003** (-3.681)	**-.004** (-2.873)							.042 [.086]
Panel B: models without autoregressive term									
11									.04 [.13]
12	**-.003** (-4.156)								.04 [.1]
13		**-.010** (-7.045)							.04 [.084]
14			**-.000** (-3.804)						.048 [.135]
15				**.080** (2.018)					.046 [.119]
16					**.365** (8.167)				.055 [.156]
17						**-.003** (-6.298)			.042 [.096]
18							**-.003** (-5.79)		.04 [.098]
19								**-.003** (-5.2)	.039 [.112]
20	**-.003** (-2.724)	**-.004** (-2.528)							.039 [.087]

Table V. Forecasting quantile regressions of the labor market conditions (MVaR95%)

Notes: This table reports main regression results for the VaR95% of the labor market conditions (the US unemployment rate multiplied by (-1)). Statistically significant coefficients (at 5%) appear in bold. The coefficients and the t-statistics for the constant and the control variables do not appear (Panels A and B) as well as the autoregressive term (Panel A). Systemic risk measures considered are respectively (from left to right): the Ted Spread (difference between the interest rate on three months' uncollateralized interbank LIBOR loans and the interest rates on Treasury bills), the default spread (yield difference between Moody's BAA and AAA corporate bonds), the VIX (implied volatility of the S&P equity index), the CoVaR, the marginal expected shortfall, the Financial Stress Index of the Federal Reserve Bank of Kansas City (KCFSI), the Financial Stress Index of the Federal Reserve Bank of Cleveland (CFSI) and the Financial Stress Index of the Federal Reserve Bank of St Louis (STLFSI). Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2014M07. Computations by the authors.

#	TED_t (*t*-stat)	DEF_t (*t*-stat)	VIX_t (*t*-stat)	$CoVaR_t$ (*t*-stat)	MES_t (*t*-stat)	$Stress1_t$ (*t*-stat)	$Stress2_t$ (*t*-stat)	$Stress3_t$ (*t*-stat)	Hit Freq. [Hit Size]
Panel A: models with autoregressive term									
1									.048
									[2.989]
2	**-.101**								.046
	(-5.043)								[1.666]
3		**-.214**							.04
		(-5.588)							[1.766]
4			**-.007**						.042
			(-3.168)						[2.056]
5				**3.566**					.042
				(3.14)					[1.697]
6					**2.585**				.044
					(2.819)				[1.946]
7						**-.081**			.04
						(-8.045)			[1.465]
8							**-.074**		.042
							(-5.521)		[1.865]
9								**-.098**	.04
								(-6.235)	[1.314]
10	**-.038**	**-.145**							.042
	(-1.986)	(-4.336)							[1.574]
Panel B: models without autoregressive term									
11									.04
									[16.045]
12	**-.806**								.042
	(-5.641)								[1.838]
13		**-2.601**							.037
		(-11.562)							[5.814]
14			**-.130**						.042
			(-8.051)						[11.375]
15				**1.543**					.039
				(.209)					[17.179]
16					**1.881**				.042
					(.305)				[17.095]
17						**-.644**			.04
						(-14.294)			[6.311]
18							**-.898**		.042
							(-19.351)		[6.618]
19								**-.674**	.039
								(-9.16)	[6.355]
20	.013	**-2.749**							.042
	(.867)	(-13.21)							[7.693]

Table VI. Long sample forecasting quantile regressions of the industrial production growth (MVaR95%)

Notes: This table reports the results of the univariate predictive quantile regressions of the industrial production growth 5th percentile based on the default spread on a very long sample covering nearly one century. We present for this long sample, as well as for various sub-samples, the coefficients, the boot-strapped t-statistics, the frequency of Hits and the size of Hits. Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1919M1 to 2014M7. Computations by the authors.

#	Sample	*Const.* (t-stat)	DEF_t (t-stat)	SR_t (t-stat)	Hit Freq. [Hit Size]
1	1919M1 - 2014M7	-.002	**.543**	**-.016**	.051
		(-1.131)	(1.320)	(-1.976)	[.712]
2	1945M1 - 2014M7	**-.013**	**.655**	**-.000**	.050
		(-7.431)	(9.565)	(-2.214)	[.421]
3	1975M1 - 2014M7	-.002	**.333**	**-.006**	.048
		(-.848)	(3.065)	(-4.316)	[.095]
4	1990M1 - 2014M7	.002	.175	**-.009**	.051
		(1.013)	(1.546)	(-5.549)	[.065]

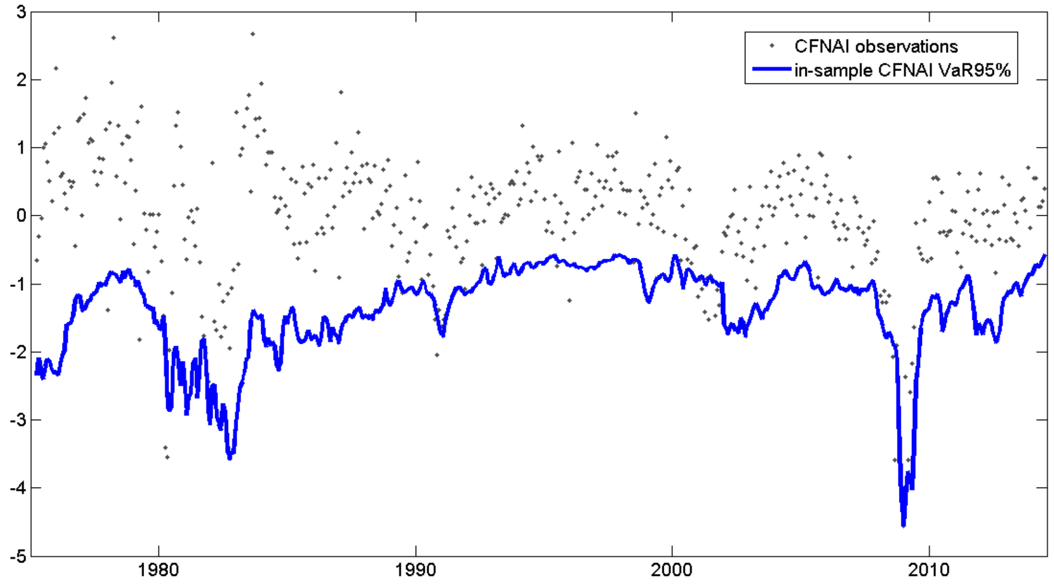

Figure 1. The figure depicts the Chicago Fed National Activity Index (represented by dots) and the in-sample forecast of the CFNAI VaR95% (the line). The forecasting model only includes a constant and an individual financial stress variable: the default spread (the difference between yields on BAA and AAA corporate bonds). Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2014M7. Computations by the authors.

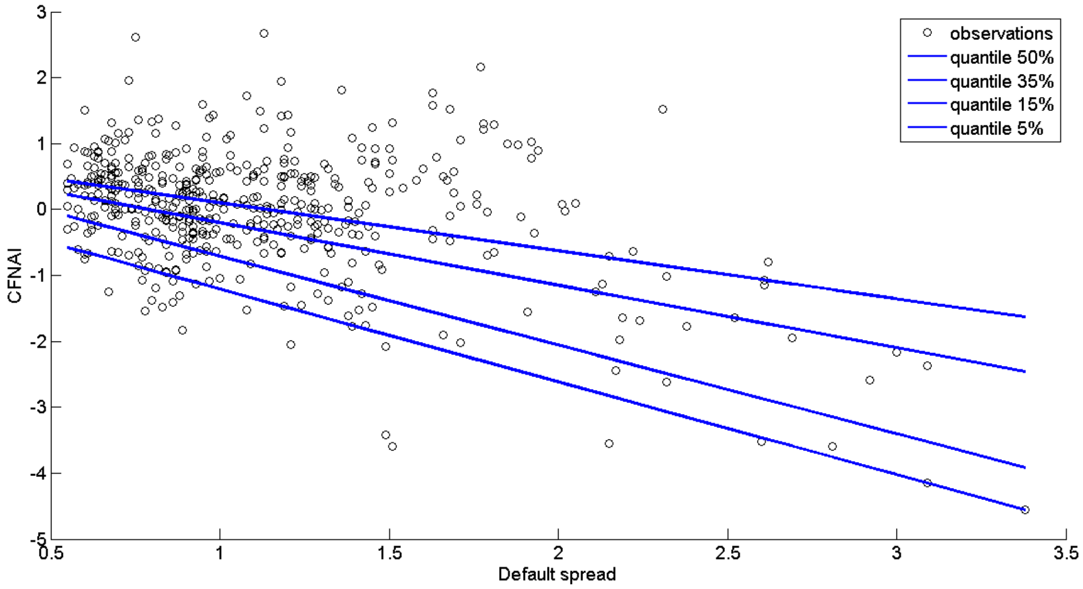

Figure 2. The figure represents the scatterplot of the monthly CFNAI (y-axis) against the lagged default spread over the period (x-axis) and the fitted conditional quantile lines for a range of quantiles between the 5th to the 50th percentile. Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M1 to 2014M7. Computations by the authors.

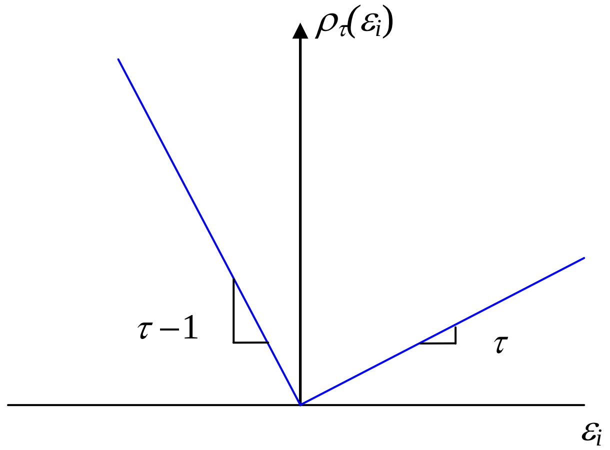

Figure 3. This figure is an illustration of the quantile regression function $\rho_\tau(\cdot)$ based on Koenker and Basset (1978). The quantile regression involves minimizing the sum of asymmetrically weighted residuals, ε_i, defined as $y_i - \xi$ (see equation 1). For example, setting $\tau = ½$ yields the median (or the minimum distance estimator). For $\tau = .05$, the result is the 5th percentile, that is the quantile corresponding to the VaR 95% in our main applications.

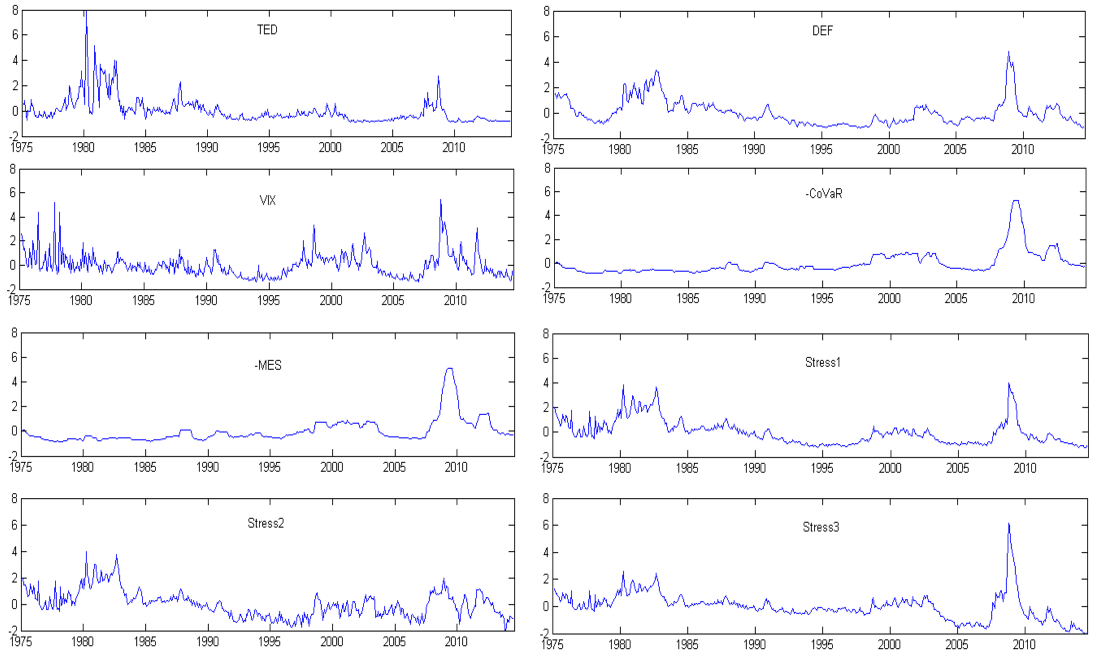

Figure 4. This figure plots the monthly time series of the z-scores of the individual and aggregate systemic risk measures from 1975M3 to 2014M7. To facilitate comparisons we represent the z-score of the inverse marginal expected shortfall (*–MES*) and the *CoVaR* (*– CoVaR*). Systemic risk measures considered are respectively (from left to right): the Ted Spread (difference between the interest rate on three months' uncollateralized interbank LIBOR loans and the interest rates on Treasury bills), the default spread (yield difference between Moody's BAA and AAA corporate bonds), the VIX (implied volatility of the S&P equity index), the CoVaR, the marginal expected shortfall, the Financial Stress Index of the Federal Reserve Bank of Kansas City (KCFSI), the Financial Stress Index of the Federal Reserve Bank of Cleveland (CFSI) and the Financial Stress Index of the Federal Reserve Bank of St Louis (STLFSI). Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M1 to 2014M7. Computations by the authors

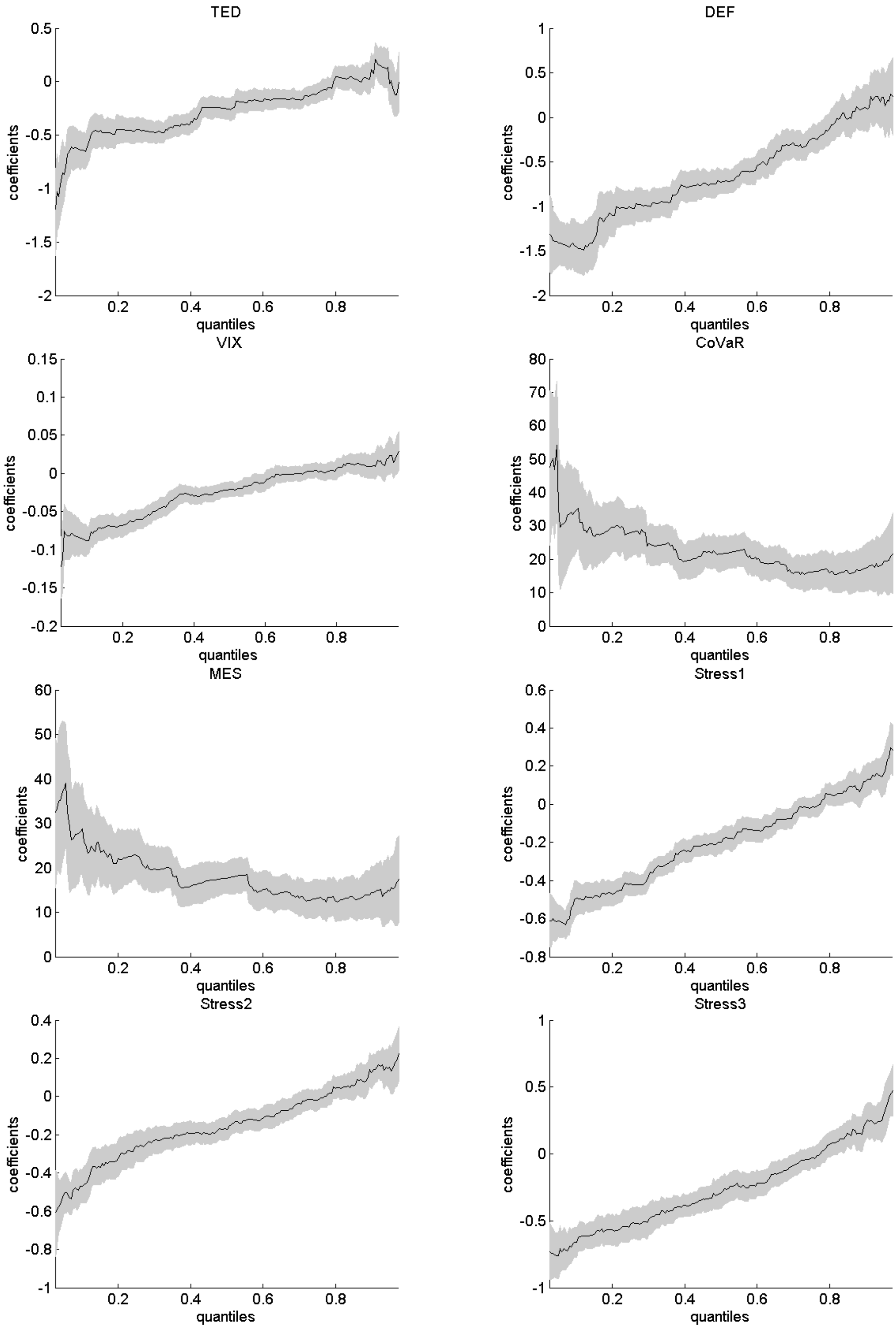

Figure 5. These figures present the slopes of the predictive univariate regressions of the CFNAI on various lagged financial distress measures, as well as the 95% confidence interval (based on bootstrapped standard errors) for the various percentiles between 2.5% and 97.5%. Systemic risk measures considered are respectively (from left to right): the Ted Spread (difference between the interest rate on three months' uncollateralized interbank LIBOR loans and the interest rates on Treasury bills), the default spread (yield difference between Moody's BAA and AAA corporate bonds), the VIX (implied volatility of the S&P equity index), the CoVaR, the marginal expected shortfall, the Financial Stress Index of the Federal Reserve Bank of Kansas City (KCFSI), the Financial Stress Index of the Federal Reserve Bank of Cleveland (CFSI) and the Financial Stress Index of the Federal Reserve Bank of St Louis (STLFSI). Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M1 to 2014M7. Computations by the authors.

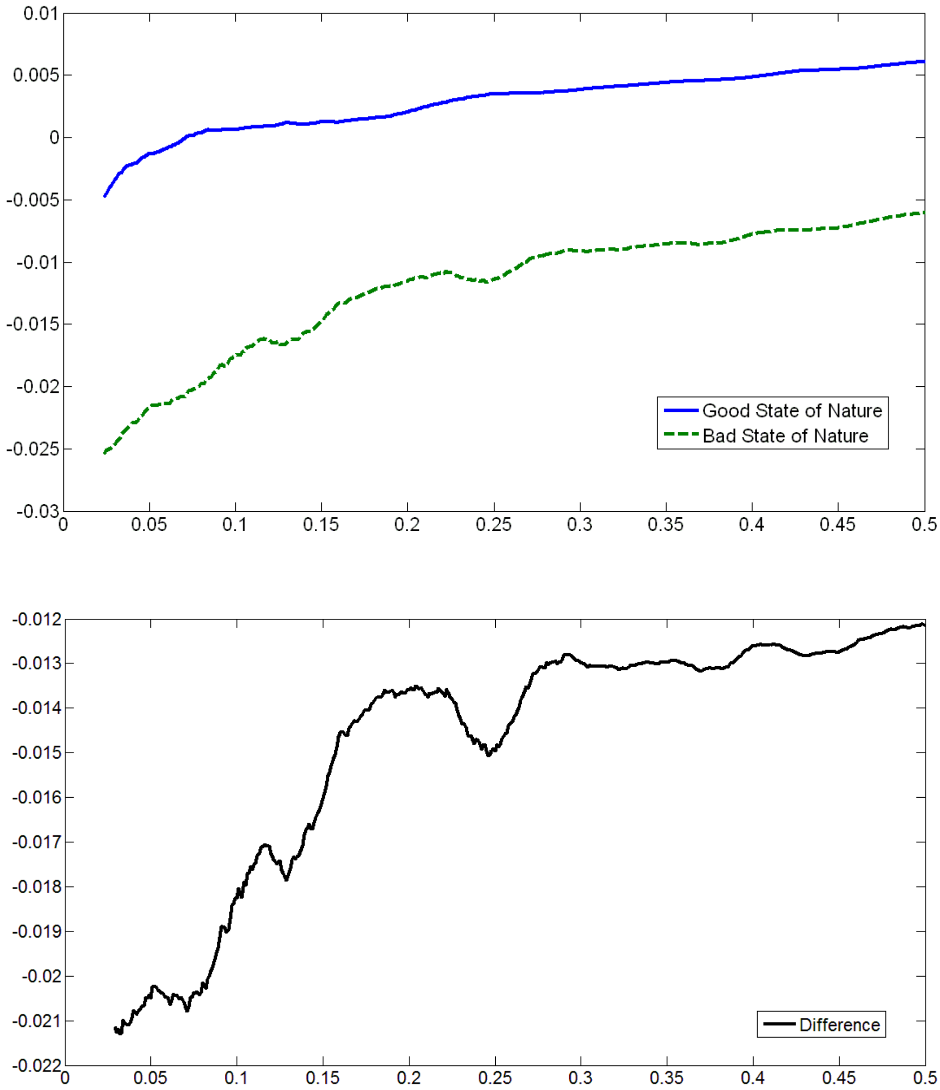

Figure 6. These figures represent the predicted quantiles (from 2.5% to 50%) of CFNAI in two states of nature – in the upper figure, as well as their difference – in the bottom figure. The "good state of nature" and the "bad state of nature" (in the upper figure) correspond, respectively, to the predicted quantiles in March 2006 and October 2008. Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2014M7. Computations by the authors.

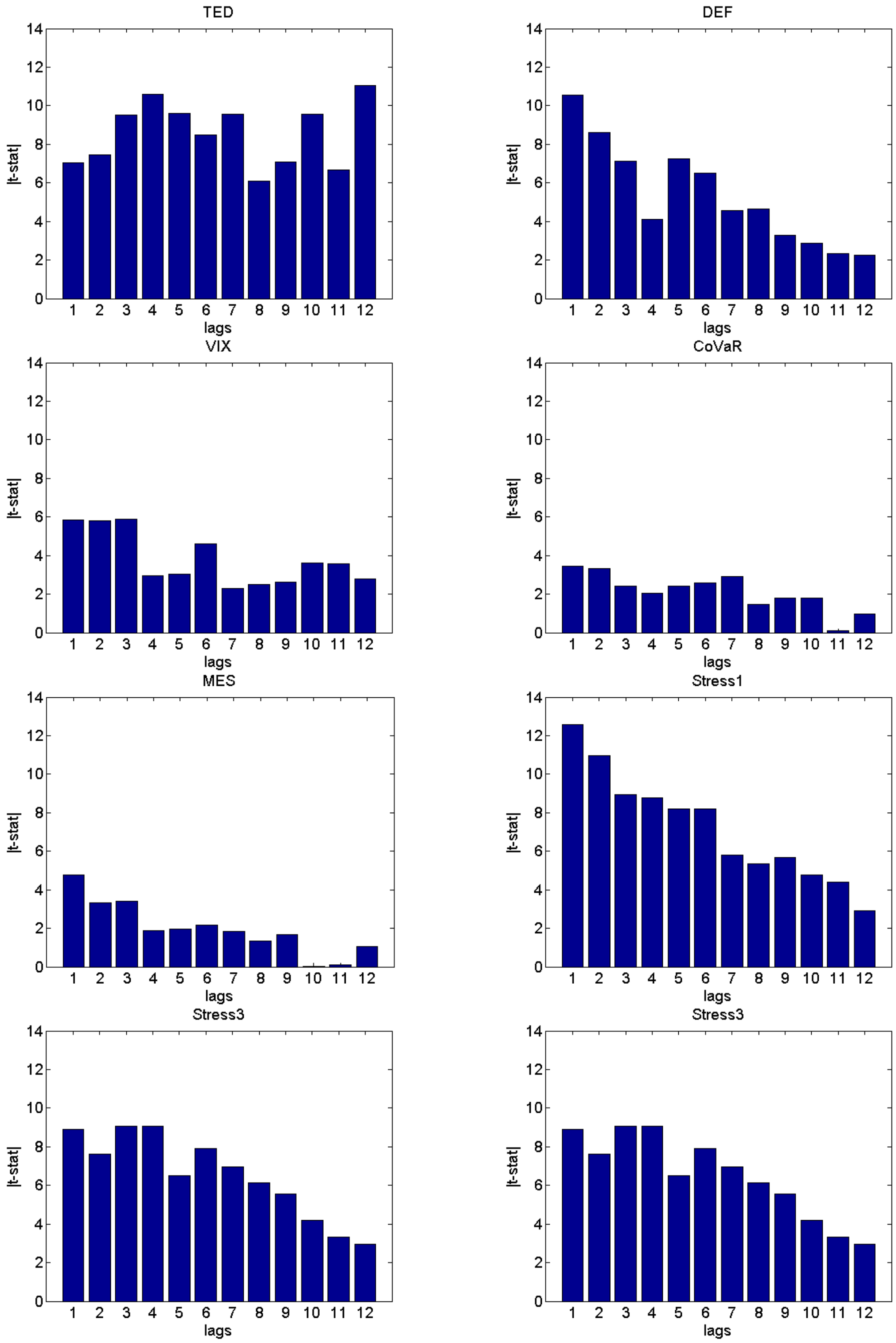

Figure 7. These figures present the absolute values of the bootstrapped t-stats for each potential predictor, i.e. systemic risk measures, with various lags considered, using univariate forecasting quantile regression models for the CFNAI 5th percentile (including a constant). Systemic risk measures considered are respectively (from left to right): the Ted Spread (difference between the interest rate on three months' uncollateralized interbank LIBOR loans and the interest rates on Treasury bills), the default spread (yield difference between Moody's BAA and AAA corporate bonds), the VIX (implied volatility of the S&P equity index), the CoVaR, the marginal expected shortfall, the Financial Stress Index of the Federal Reserve Bank of Kansas City (KCFSI), the Financial Stress Index of the Federal Reserve Bank of Cleveland (CFSI) and the Financial Stress Index of the Federal Reserve Bank of St Louis (STLFSI). Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M1 to 2014M7. Computations by the authors.