Systemic Risk and the Macroeconomy: An Empirical Evaluation*

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October 2013

Abstract

We propose an empirical criterion for evaluating systemic risk measures based on their ability to predict quantiles of future macroeconomic shocks. We construct 17 measures of systemic risk in the US and Europe spanning several decades. We propose dimension reduction estimators for constructing systemic risk indexes from the cross section of measures and prove their consistency in a factor model setting. Empirically, systemic risk indexes provide significant predictive information for the lower tail of future macroeconomic shocks, even out-of-sample.

Keywords: systemic risk, systemic risk measures, quantile regression, dimension reduction, macroeconomic welfare

*We thank Lars Hansen for many helpful conversations about this project. We also thank Tobias Adrian, John Cochrane, Doug Diamond, Rochelle Edge, Arvind Krishnamurthy, Nellie Liang, Amir Sufi, Amit Seru, Allan Timmermann, Jonathan Wright and seminar participants at the Federal Reserve Board, the Federal Reserve Bank of San Francisco, University of Chicago (Booth), and the NBER 2013 Summer Institute EFWW group for helpful comments. We thank Xiao Qiao for excellent research assistance and Roger Koenker, Andrew Lo, Christian Brownlees and Mark Flood for sharing Matlab code. The viewpoints in this paper are those of the authors and do not necessarily represent those of the Board of Governors of the Federal Reserve System or its staff.

1 Introduction

Many systemic risk measures have been proposed in the aftermath of the 2007-2009 financial crisis. While individual measures are explored in separate papers, there has been little empirical analysis of them as a group. In this paper we have three complementary objectives for establishing an empirical understanding of the compendium of systemic risk measures and for guiding future research.[1]

Our first goal is to provide a basic quantitative description of existing systemic risk measures. We examine 17 previously proposed measures of systemic risk in the US and 10 measures for the UK and Europe. In building these measures, we use the longest possible data history, which in some cases allows us to use the entire postwar sample in the US. To the extent that systemically risky episodes are rarely observed phenomena, our longer time series and international panel provide robust empirical insights over several business cycles, in contrast to much of the systemic risk literature's emphasis on the last five years in the US.

The absence of a clear criterion to judge the performance of systemic risk measures has made it difficult to establish empirical patterns among the many papers in this area. Our second objective is to fill this gap by proposing a new criterion for evaluating systemic risk measures. While there are many potential criteria to consider, such as their usefulness for risk management by financial institutions or their ability to forecast asset price fluctuations, we take a take a macroeconomic policy stance in defining our criterion. We argue that to be included as an input for macroprudential regulation or policy-making, a systemic risk measure should be informative about future economic welfare. In particular, policy-makers should only rely on a systemic risk measure insofar as it predicts real macroeconomic activity such as production, employment or consumption.[2]

To operationalize this criterion we propose the use of predictive quantile regression, which estimates how the distribution of future macroeconomic variables responds to systemic risk. We argue that a quantile approach is appropriate for evaluating the

[1]Bisias et al. (2012) provide an excellent survey of systemic risk measures. Their overview is qualitative in nature – they collect detailed definitions of measures but do not analyze data. Our analysis is quantitative.

[2]A systemic risk measure that does not possess explanatory power for real macroeconomic aggregates is still a potentially valid tool for other endeavors, such as understanding the degree of risk in financial markets. But if such a measure does not ultimately correlate with real outcomes, we argue that it need not enter the decision rule of a policy-maker.

potentially non-linear association between systemic risk and the macroeconomy that has been emphasized in the theoretical literature.[3] These theories predict that distress in the financial system can amplify adverse fundamental shocks and result in severe downturns or crises. Quantile regression is a flexible tool for investigating differential impacts of systemic risk on the central tendency and tail behavior of macroeconomic shocks.

Our third goal is to determine whether statistical dimension reduction techniques can detect a robust relationship between systemic risk measures and the macroeconomy, above and beyond the information in potentially noise-ridden individual measures. While dimension reduction techniques have been widely studied in the least squares macro-forecasting literature, we focus on dimension reduction techniques for quantile regression. We pose the following statistical problem. Suppose all systemic risk measures are imperfectly measured versions of an unobservable systemic risk factor. Furthermore, suppose that the conditional quantiles of macroeconomic variables also depend on the unobserved factor. How may we identify this latent factor that drives both measured systemic risk and the distribution of future macroeconomic shocks? We propose two dimension reduction estimators to solve this problem.

The first estimator is principal components quantile regression (PCQR). This two step procedure first extracts principal components from the panel of systemic risk measures and then uses these factors in predictive quantile regressions. We prove that this approach consistently estimates conditional quantiles of macroeconomic shocks under mild conditions.[4] We then propose an alternative estimator called partial quantile regression (PQR) that is an adaptation of partial least squares to the quantile setting. We prove the new result that PQR produces consistent quantile forecasts, and often achieves consistency with fewer extracted factors than PCQR.[5]

[3] See, for example, Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Bernanke, Gertler and Gilchrist (1999), Brunnermeier and Sannikov (2010), Gertler and Kiyotaki (2010), Mendoza (2010), and He and Krishnamurthy (2012).

[4] The use of principal components to aggregate information among a large number of predictor variables is well-understood for least squares forecasting – see Stock and Watson (2002) and Bai and Ng (2006). The use of principal components in quantile regression has been proposed by Ando and Tsay (2011).

[5] The key difference between PQR and PCQR is their method of dimension reduction. PQR condenses the cross section according to each predictor's quantile covariation with the forecast target, choosing a linear combination of predictors that is optimal for quantile forecasting. On the other hand, PCQR condenses the cross section according to covariance within the predictors, disregarding how closely each predictor relates to the target. Dodge and Whittaker (2009) discuss a version of PQR but do not analyze its sampling properties.

A set of new stylized facts emerge from our empirical investigation. First, we find that few systemic risk measures possess significant predictive content for the downside quantiles of macroeconomic shocks (such as innovations in industrial production and the Chicago Fed National Activity Index). Notable exceptions are measures of financial sector equity volatility, which do capture changes in downside risk. This result highlights that systemic risk is a multifaceted phenomenon. While all the measures used in this paper have been shown to successfully capture different aspects of financial sector stress, they individually they have a hard time identifying the effect of distress on macroeconomic outcomes. We proceed to test the macroeconomic predictive power of our dimension reduction estimators that use the cross section of systemic risk variables to construct a parsimonious set of systemic risk indexes. PQR achieves significant forecast improvements across macroeconomic variables in a wide range of specifications, and PCQR is competitive in a subset of our analyses.

Overall, our empirical results reach a positive conclusion regarding the empirical systemic risk literature. We demonstrate that, when taken as a whole, the compendium of systemic risk measures indeed contains useful predictive information about future macroeconomic outcomes, despite the individual failure of many measures on this account. This conclusion is based on out-of-sample tests and is robust across a range of lower quantiles, across macroeconomic variables, and across the US, UK and Europe. We also find that the relationship between systemic risk and future macroeconomic shocks is much stronger in the lower tail than in the center of the distribution. Systemic risk indexes predict movements in the lower tail (the 10^{th} and 20^{th} percentile) of macroeconomic outcomes, but not the mean or median.

We also find that financial sector equity volatility exhibits strong univariate predictive power for the quantiles of future real outcomes. In contrast, equity volatility in non-financial sectors appears to have little, if any, predictive power. We demonstrate that financial sector volatility plays a special role in explaining macro fluctuations not only in our quantile regression setting, but also in the least squares VAR analysis of Bloom (2009). This suggests that economic mechanisms connecting stock market volatility to the real economy, such as the uncertainty shocks mechanism in Bloom (2009), may blur an important distinction between financial uncertainty and uncertainty in other industries.

Finally, systemic risk indicators predict policy decisions. When systemic risk rises, governments may respond with intervention that averts negative macro shocks.

Indeed, we find that high levels of systemic risk indexes predict decreases in the Federal Funds rate. If policy is effective, however, we would find no association between systemic risk measures and future outcomes in the real economy. While the Federal Funds rate responds to systemic risk, it does not fully counteract downside macroeconomic risk, since we also find a strong association between systemic risk and the low quantiles of macroeconomic outcomes. This implies that there may be scope for expanded policy actions that explicitly respond to systemic risk identified from financial markets.

The remainder of the paper proceeds as follows. Section 2 defines and provides a quantitative description of a set of systemic risk measures in the US and Europe. In Section 3, we examine the power of these measures for predicting quantiles of macroeconomic shocks using univariate quantile regressions. In Section 4, we define PCQR and PQR, prove their consistency and use them to form predictive systemic risk indexes with robust predictive power for the future distribution of macroeconomic shocks. Section 5 discusses stylized facts based on our empirical results. Section 6 concludes. The appendices collect proofs and supporting material.

2 A Quantitative Survey of Systemic Risk Measures

2.1 Data Sources for Systemic Risk Measures

This section outlines our construction of systemic risk measures and provides a brief summary of comovement among measures. US measures are based on data for financial institutions identified by 2-digit SIC codes 60 through 67 (finance, insurance and real estate).[6] We obtain equity returns for US financial institutions from CRSP and we obtain book data from Compustat.

We also construct measures for the UK and Europe. Our "EU" measures pool data on financial institution equity returns from France, Germany, Italy and Spain, the largest continental European Union economies. UK and EU returns data are obtained from Datastream.[7] We do not construct measures that require book data

[6]This definition of financial sector corresponds to that commonly used in the literature (see, e.g., Acharya et al. (2010)).

[7]Datastream data requires cleaning. We apply the following filters. 1) When a firm's data series ends with a string of zeros, the zeros are converted to missing, since this likely corresponds to a firm exiting the dataset. 2) To ensure that we use liquid securities, we require firms to have non-zero returns for at least one third of the days that they are in the sample, and we require at least

for the UK and EU, nor do we have data for some other counterparts to US measures such as the default spread.

2.2 Overview of Measures

Bisias et al. (2012) categorize and collect definitions of more than 30 systemic risk measures. We build measures from that survey to the extent that we have access to requisite data. Below we provide a brief overview of the measures that we build grouped by their defining features. We refer readers to Appendix B.1 and to Bisias et al. (2012) for additional details.

We are interested in capturing systemic risk stemming from the core of the financial system, and thus construct our measures using data for the 20 largest financial institutions in each region (US, UK, and EU) in each period.[8] Whenever the systemic risk measure is constructed from an aggregation of individual measures (for example in the case of CoVaR, which is defined at the individual firm level), we compute the measure for each of the 20 largest institutions in each period and take an equal weighted average. The only exception is the size concentration of the financial sector for which we use the largest 100 institutions (or all institutions if they number fewer than 100). Table 1 shows the available sample for each measure by region.

2.2.1 Institution-Specific Risk

Institution-specific measures are designed to capture an individual bank's contribution or sensitivity to economy-wide systemic risk. These measures include CoVaR and ΔCoVaR from Adrian and Brunnermeier (2011), marginal expected shortfall (MES) from Acharya, Pedersen, Philippon and Richardson (2010), and MES-BE, a version of marginal expected shortfall proposed by Brownlees and Engle (2011).

2.2.2 Comovement and Contagion

Comovement and contagion measures quantify dependence among financial institution equity returns. We construct the Absorption Ratio described by Kritzman et al. (2010), which measures the fraction of the financial system variance explained

three years of non-zero returns in total. 3) We winsorize positive returns at 100% to eliminate large outliers that are likely to be recording errors.

[8] If less than 20 institutions are available, we construct measures from all available institutions, and if data for fewer than ten financial institutions are available the measure is treated as missing.

by the first K principal components (we use $K = 3$). We also construct the Dynamic Causality Index (DCI) from Billio et al. (2012) which counts the number of significant Granger-causal relationships among bank equity returns, and the International Spillover Index from Diebold and Yilmaz (2009) which measures comovement in macroeconomic variables across countries.[9]

2.2.3 Volatility or Instability

To quantify system instability, we compute the average equity volatility of the largest 20 financial institutions. We also compute their aggregate book leverage and market leverage, size concentration in the financial industry (the market equity Herfindal index), and financial sector turbulence, a measure that is conceptually similar to volatility.

2.2.4 Liquidity and Credit

Liquidity and credit conditions in financial markets are measured by Amihud's (2002) illiquidity measure (AIM) aggregated across financial firms, the TED spread (LIBOR minus the T-bill rate), the default spread (BAA bond yield minus AAA bond yield), and the term spread (the slope of the Treasury yield curve).

2.2.5 Measures Not Covered

Due to data constraints, particularly in terms of time series length, we do not include measures of linkages between financial institutions (such as interbank loans or derivative positions), stress tests, or credit default swap spreads.

2.3 Macroeconomic Data

Our analysis focuses on real macroeconomic shocks measured by industrial production (IP) growth in the US, UK and EU. These data come from the Federal Reserve Board for the US and OECD for the UK and EU.[10] Our sample for the US is the entire

[9] We do not include the volatility connectedness measure of Diebold and Yilmaz (forthcoming). Arsov et al. (2013) shows that this is a dominant leading indicator of financial sector stress in the recent crisis. Unfortunately, the Diebold-Yilmaz index is only available beginning in 1999 and thus does not cover a long enough time series to be included in our tests.

[10] For the EU, we use the OECD series for the 17 country Euro zone.

postwar era 1946-2011.[11] For the UK, data begin in 1978. Our EU sample begins in 1994.

In robustness checks, we consider US macroeconomic shocks measured by the Chicago Fed National Activity Index (CFNAI) and its subcomponents: production and income (PI), employment, unemployment and hours (EUH), personal consumption and housing (PH) and sales, and orders and inventory (SOI). These data come from the Federal Reserve Bank of Chicago and are available beginning in 1967.

Our focus is on how systemic risk affects the distribution of future macroeconomic shocks. We define macro shocks as innovations to an autoregression in the underlying macroeconomic series.[12] This strips out variation in the target variable that is forecastable using its own history, following the forecasting literature such as Bai and Ng (2008b) and Stock and Watson (2012). We choose the autoregressive order based on the Akaike Information Criterion (AIC) for each series – typical orders are between 3 and 6 in our monthly data – and perform the autoregression estimation (including the AIC-based model selection) recursively out-of-sample.[13] Finally, we aggregate monthly shocks into a quarterly shock by summing monthly innovations in order to put the targets on a forecast horizon that is relevant for policy-makers. Further details are available in Appendix B.2.

Preliminary autoregressions absorb much of the standard business-cycle variation in our forecast targets, and thus allow us to focus attention on macroeconomic downturns whose origins reside in financial markets and financial distress when we conduct our main quantile tests. We also performed our analysis with more thorough pre-whitening in the form of autoregressions augmented to include lagged principal components from Stock and Watson's (2012) data. This produces minor quantitative changes to our results and does not alter any of our conclusions.

[11] Industrial production begins in the 1910's, but following the bulk of macroeconomic literature we focus on the US macroeconomy following World War II.

[12] An alternative to pre-whitening is to conduct Granger causality tests that control for lags of the dependent variable. Appendix B.3 shows that Granger causality tests broadly agree with our findings based on autoregression residuals.

[13] Using the full-sample AR estimate in out-of-sample quantile forecasts has little effect on our results, as the recursively-estimated AR projection is stable after only a few years of observations.

2.4 Summary of Comovement Among Systemic Risk Measures

Figure 1 plots the monthly time series of select measures in the US.[14] All measures spiked during the recent financial crisis, which is not surprising given that many of these measures were proposed *post hoc*. In earlier episodes, many systemic risk measures reached similar levels to those experienced during the recent crisis. During the oil crisis and high uncertainty of the early and mid 1970's, financial sector market leverage and return turbulence spike. All the measures display substantial variability and several experience high levels in non-recessionary climates. One interpretation of the plot is that these measures are simply noisy. Many of the spikes that do not seem to correspond to a financial crisis might be considered "false positives." Another interpretation is that these measures sometimes capture stress in the financial system that does not result in full-blown financial crises, either because policy and regulatory responses diffused the instability or the system stabilized itself (we discuss this further in Section 5.3). Yet another interpretation is that crises develop only when many systemic risk measures are simultaneously elevated, as during the recent crisis.

Table 2 shows correlations among different measures for the US, UK and EU. Most correlations are quite low. Only small groups of measures comove strongly. For example, turbulence, volatility, and the TED spread are relatively highly correlated. Similarly, CoVaR, ΔCoVaR, MES and Absorption tend to comove. The other measures display low or even negative correlations with each other, suggesting that many measures capture different aspects of financial system stress or are subject to substantial noise. If low correlations are due to the former, then our tests for association between systemic risk measures and macroeconomic outcomes can help distinguish which aspects of systemic risk are most relevant from a policy standpoint.

Finally, some measures of systemic risk may be interpreted as *contemporaneous* stress indicators and others as *leading indicators* of systemic risk. We describe lead-lag relations between these variables by conducting two-way Granger causality tests. Table 3 reports the number of variables that each measure Granger causes (left column) or is Granger caused by (right column). ΔAbsorption, turbulence, ΔCoVaR and volatility appear to behave as leading indicators in that they frequently Granger

[14]For readability, the plotted measures are standardized to have the same variance (hence no y-axis labels are shown) and we only a show a subset of the series we study.

cause other variables and not the reverse. The term spread, the international spillover index, MES, MES-BE and DCI tend to lag other measures and thus may be viewed as coincident indicators of a systemic shock. These associations appear consistent across countries.

3 Systemic Risk Measures and the Macroeconomy

The previous section documents heterogeneity in the behavior of systemic risk measures. Without a clear criterion it is difficult to judge their relative merits. Our criterion seeks to quantify the relevance of each of these risk measures for forecasting real economic outcomes. In particular, we investigate which systemic risk measures give policy-makers significant information about the distribution of future macroeconomic shocks. We believe this criterion improves our understanding of systemic risk in two dimensions. It highlights the field's need for an empirical description of linkages between the array of proposed financial sector stress indicators and macroeconomic outcomes, and it provides a new tool for evaluating policy relevance when selecting among a pool of candidate systemic risk measures.

The basic econometric tool for our analysis is predictive quantile regression, which we use to judge the relationship of a systemic risk measure to future economic activity. We view quantile regression as a flexible statistical tool for investigating potentially non-linear dynamics between systemic risk and economic outcomes. Such a reduced-form statistical approach has benefits and limitations. Benefits include potentially less severe specification error and, most importantly, the provision of new empirical descriptions to inform future theory. A disadvantage is the inability to identify "fundamental" shocks or specific mechanisms as in a structural model. Hansen (2013) provides an insightful overview of advantages to systemic risk modeling with and without the structure of theory.

3.1 Quantile Regression

Before describing our empirical results we offer a brief overview of the econometric tools and notation that we use. Denote the target variable as y_{t+h}, a scalar real macroeconomic shock whose conditional quantiles we wish to capture with systemic risk measures. Let h be some positive integer. The τ^{th} quantile of y_{t+h} is its inverse probability distribution function, denoted

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

The quantile function may also be represented as the solution to an optimization problem

$$\mathbb{Q}_\tau(y_{t+h}) = \arg\inf_q E[\rho_\tau(y_{t+h} - q)]$$

where $\rho_\tau(x) = x(\tau - I_{x<0})$ is the quantile loss function.

Previous literature shows that this expectation-based quantile representation is convenient for handling conditioning information sets and deriving a plug-in M-estimator. In the seminal quantile regression specification of Koenker and Bassett (1978), the conditional quantiles of y_{t+h} are affine functions of observables $\boldsymbol{x}_t$,

$$\mathbb{Q}_\tau(y_{t+h}|\mathcal{I}_t) = \beta_{\tau,0} + \boldsymbol{\beta}'_\tau \boldsymbol{x}_t. \tag{1}$$

An advantage of quantile regression is that the coefficients $\beta_{\tau,0}, \boldsymbol{\beta}_\tau$ are allowed to differ across quantiles.[15] Thus quantile models can provide a richer picture of the target distribution when conditioning information shifts more than just the distribution's location. As Equation 1 suggests, we focus on quantile forecasts rather than contemporaneous regression since leading indicators are most useful from a policy and regulatory standpoint.

Fits can be evaluated via a quantile R^2 based on the loss function ρ_τ,

$$R^2 = 1 - \frac{\frac{1}{T}\sum_t[\rho_\tau(y_{t+1} - \hat{\alpha} - \hat{\beta}X_t)]}{\frac{1}{T}\sum_t[\rho_\tau(y_{t+1} - \hat{q}_\tau)]}.$$

This expression captures the typical loss using conditioning information (the numerator) relative to the loss using the historical unconditional quantile estimate (the denominator). The in-sample R^2 lies between zero and one. Out-of-sample, the R^2 can go negative if the historical unconditional quantile offers a better forecast than the conditioning variable. In sample, we report the statistical significance of the predictive coefficients as found by Wald tests (or t-statistics for univariate regressions)

[15] Chernozhukov, Fernandez-Val and Galichon (2010) propose a monotone rearranging of quantile curve estimates using a bootstrap-like procedure to impose that they do not cross in sample. We focus attention on only the $10^{th}, 20^{th}$ and 50^{th} percentiles and these estimates never cross in our sample.

using standard errors from the residual block bootstrapped using block lengths of six months and 1,000 replications. Out of sample, we arrive at a description of statistical significance for estimates by comparing the sequences of quantile forecast losses based on conditioning information, $\rho_\tau(y_{t+1} - \hat{\alpha} - \hat{\beta}X_t)$, to the quantile loss based on the historical unconditional quantile, $\rho_\tau(y_{t+1} - \hat{q}_\tau)$, following Diebold and Mariano (1995) and West (1996).

Our benchmark results focus attention on the 20^{th} percentile, or $\tau = 0.2$. This choice represents a compromise between the conceptual benefit of emphasizing extreme regions of the distribution and the efficiency cost of using too few effective observations. In robustness checks we show that results for the 10^{th} percentile are similar. In addition to tail quantiles, we also estimate median regressions ($\tau = 0.5$) to study systemic risk impacts on the central tendency of macroeconomic shocks.

3.2 Empirical Evaluation of Systemic Risk Measures

Table 4 Panel A reports the quantile R^2 from in-sample 20^{th} percentile forecasts of IP growth shocks in the US, UK and EU using the collection of systemic risk measures. Our main analysis uses data from 1946-2011 for the US, 1978-2011 for the UK, and 1994-2011 for the EU.

In sample, a wide variety of systemic risk measures demonstrate large predictive power for the conditional quantiles for IP growth shocks in various countries. Looking across countries, CoVaR, ΔCoVaR, MES, default spread and volatility provide substantial predictive information across all regions. This picture changes when we look out-of-sample.

Table 5 Panel A reports recursive out-of-sample predictive statistics. The earliest out-of-sample start dates are 1950 for the US, 1990 for the UK, and 2000 for the EU (due to the shorter data samples outside the US). We take advantage of the longer US time series to perform subsample analysis, and report results for out-of-sample start dates of 1970 and 1990 for robustness.

Most measures do not significantly outperform the historical quantile (which is also calculated recursively out-of-sample) in forecasting downside macroeconomic risk. No measure is significant for every region and start date. Volatility in the financial sector shows the best overall performance. It has a positive R^2 in all samples, but is statistically insignificant for the EU.

Focusing on the US, Table 5 Panel A shows that AIM, volatility and turbulence are informative out-of-sample for any split date. Table 6 Panel A investigates the robustness of this observation to different measures of macroeconomic shocks coming from the CFNAI series. There we see that only turbulence provides significant out-of-sample predictive content for the total CFNAI index and each of its component series, although market leverage is broadly significant as well.[16]

Table 7 Panel A reports that US results are broadly similar if we study the 10^{th} rather than the 20^{th} percentile of IP growth. AIM, volatility and turbulence continue to show significant predictive power. Table 8 Panel A reports that volatility and turbulence also demonstrate predictive power for the 10^{th} percentile across shocks measured by the CFNAI, and that market leverage is broadly significant as well. Our benchmark findings based on the 20^{th} percentile are thus broadly consistent with more extreme quantiles.

Turning to the central tendency of macroeconomic shocks, Table 9 Panel A shows that no systemic risk measure consistently demonstrates forecast power for the median shock across samples. Volatility and turbulence possess some predictive power for the median, but substantially more power for the 10^{th} and 20^{th} percentiles.

In summary, we find that few systemic risk measures possess robust power to forecast downside macroeconomic quantiles. The exceptions are measures of financial sector volatility, especially turbulence. To the extent that we find any forecasting power, it is stronger for the lower quantiles of macroeconomic shocks than for their central tendency.

4 Systemic Risk Indexes and the Macroeconomy

Individually, most systemic risk measures lack a strong statistical association with macroeconomic downside risk. This could be because measurement noise obscures the useful content of these series, or because different measures capture different aspects of systemic risk. Is it possible, then, to combine these measures into a more informative systemic risk index?

In this section we propose a statistical model in which the conditional quantiles of y_{t+h} depend on a low-dimension unobservable factor f_t, and each individual systemic risk variable is a noisy measurement of f_t. This structure suggests that dimension

[16] The CFNAI is available 1967-2011 and we set the out-of-sample start date to 1975.

reduction techniques may be helpful in extracting information about future macroeconomic shocks from the cross section of individual systemic risk measures. The factor structure is similar to well-known conditional mean factor models (e.g. Sargent and Sims (1977), Geweke (1977), Stock and Watson (2002)). The interesting feature of our model, as in Ando and Tsay (2011), is that it links multiple observables to latent factors that drive the conditional *quantile* of the forecast target.

We present two related procedures for constructing systemic risk indexes: principal components quantile regression and partial quantile regression. We show that they consistently estimate the latent conditional quantile driven by f_t. We also show that they are empirically successful, demonstrating robust out-of-sample forecasting power for downside macroeconomic risk.

4.1 A Latent Factor Model for Quantiles

We assume that the τ^{th} quantile of y_{t+h}, conditional on an information set $\mathcal{I}_t$, is a linear function of an unobservable univariate factor f_t:[17]

$$\mathbb{Q}_\tau(y_{t+h}|\mathcal{I}_t) = \alpha f_t.$$

This formulation is identical to a standard quantile regression specification, except that f_t is latent. Realizations of y_{t+h} can be written as $\alpha f_t + \eta_{t+h}$ where η_{t+h} is the quantile forecast error. The cross section of predictors (systemic risk measures) is defined as the vector $\boldsymbol{x}_t$, where

$$\boldsymbol{x}_t = \boldsymbol{\Lambda} \boldsymbol{F}_t + \boldsymbol{\varepsilon}_t \equiv \boldsymbol{\phi} f_t + \boldsymbol{\Psi} \boldsymbol{g}_t + \boldsymbol{\varepsilon}_t.$$

Idiosyncratic measurement errors are denoted by $\boldsymbol{\varepsilon}_t$. We follow Kelly and Pruitt (2012, 2013) and allow $\boldsymbol{x}_t$ to depend on the vector $\boldsymbol{g}_t$, which is an additional factor that drives the risk measures but does not drive the conditional quantile of y_{t+h}.[18] Thus, common variation among the elements of $\boldsymbol{x}_t$ has a portion that depends on f_t and is therefore relevant for forecasting the conditional distribution of y_{t+h}, as well as a forecast-irrelevant portion driven by $\boldsymbol{g}_t$. For example, $\boldsymbol{g}_t$ may include factors

[17]We omit intercept terms to ease notation in the main text; our proofs and empirical implementations include them.

[18]We assume a factor normalization such that f_t is orthogonal to $\boldsymbol{g}_t$. For simplicity, we treat f_t as scalar, but this is trivially relaxed.

associated with stress in financial markets that never metastasizes to the real economy or that is effectively remedied by government intervention. Not only does $\boldsymbol{g}_t$ serve as a source of noise when forecasting of y_{t+h}, but it is particularly insidious because it is pervasive among predictors.

4.2 Estimators

The most direct approach to quantile forecasting with several predictors is multiple quantile regression. As in OLS with a large number of regressors, this approach is likely to lead to overfitting and poor out-of-sample performance. Therefore we propose two dimension reduction approaches that consistently estimate the conditional quantiles of y_{t+h} as the numbers of predictors and time series length simultaneously become large. We first prove each estimator's consistency and then test their empirical performance.

One can view our latent factor model as being explicit about the measurement error that contaminates each predictor's reading of f_t. The econometrics literature has proposed instrumental variables solutions and bias corrections for the quantile regression errors-in-variables problem.[19] We instead exploit the large N nature of the predictor set to deal with errors-in-variables. Dimension reduction techniques aggregate large numbers of individual predictors to isolate forecast-relevant information while averaging out measurement noise.

For the sake of exposition, we place all assumptions in Appendix A.1. They include restrictions on the degree of dependence between factors, idiosyncracies, and quantile forecast errors in the factor model just outlined. They also impose regularity conditions on the quantile forecast error density and the distribution of factor loadings.

4.2.1 Principal Components Quantile Regression (PCQR)

The first estimator is principal component quantile regression (PCQR). In this method, we extract common factors from $\boldsymbol{x}_t$ via principal components and then use them in an otherwise standard quantile regression (the algorithm is summarized in Table 10).

[19] Examples of instrumental variables approaches include Abadie, Angrist and Imbens (2002), Chernozhukov and Hansen (2008), and Schennach (2008). Examples of bias correction methods include He and Liang (2000), Chesher (2001), and Wei and Carroll (2009).

PCQR produces consistent quantile forecasts when both the time series dimension and the number of predictors become large, as long as we extract as many principal components as there are elements of $\boldsymbol{F}_t = (f_t, \boldsymbol{g_t}')'$.

Theorem 1 (Consistency of PCQR)**.** *Under assumptions 1-3, the principal components quantile regression predictor of* $\mathbb{Q}_\tau(y_{t+h}|\mathcal{I}_t) = \boldsymbol{\alpha}'\boldsymbol{F}_t = \alpha f_t$ *is given by* $\hat{\boldsymbol{\alpha}}'\hat{\boldsymbol{F}}_t$*, where* $\hat{\boldsymbol{F}}$ *represents the first* K *principal components of* $\boldsymbol{X}'\boldsymbol{X}/(TN)$*,* $K = dim(f_t, \boldsymbol{g}_t)$*, and* $\hat{\boldsymbol{\alpha}}$ *is the quantile regression coefficient on those components. For each* t*, the PCQR quantile forecast satisfies*

$$\hat{\boldsymbol{\alpha}}'\hat{\boldsymbol{F}}_t - \alpha' f_t \xrightarrow[N,T\to\infty]{p} 0.$$

The proof of Theorem 1 is in Appendix A.2. The theorem states that our estimator is consistent not for a particular regression coefficient but for the conditional quantile of y_{t+h}. As a key to our result, we adapt Angrist, Chernozhukov and Fernandez-Val's (2006) mis-specified quantile regression approach to the latent factor setting. From this we show that measurement error vanishes for large N, T.[20]

4.2.2 Partial Quantile Regression (PQR)

For simplicity, our factor model assumes that a scalar f_t comprises all information relevant for the conditional quantile of interest. But PCQR and Theorem 1 use the vector $\hat{\boldsymbol{F}}_t$ because PCQR is only consistent if the entire factor space $(f_t, \boldsymbol{g_t}')$ is estimated. This is analogous to the distinction between principal components least squares regression and partial least squares. The former produces an consistent forecast when the entire factor space is spanned, whereas the latter is consistent as long as the subspace of relevant factors is spanned (see Kelly and Pruitt (2012)).

Our second estimator is called partial quantile regression (PQR) and extends the method of partial least squares to the quantile regression setting. PQR condenses the cross section of predictors according to their quantile covariation with the forecast target, in contrast to PCQR which condenses the cross section according to covariance within the predictors. By weighting predictors based on their predictive strength, PQR chooses a linear combination that is optimal for quantile forecasting.

[20] It is possible to expand the consistency result and derive the limiting distribution of quantile forecasts, which can then be used to conduct in-sample inference. In-sample inference is not relevant for our empirical analysis, which focuses on out-of-sample forecasting.

PQR forecasts are constructed in three stages as follows (the algorithm is summarized in Table 10). In the first pass we calculate the quantile slope coefficient of y_{t+h} on each individual predictor x_i ($i = 1, ..., N$) using univariate quantile regression (denote these estimates as $\hat{\gamma}_i$).[21] The second pass consists of T covariance estimates. In each period t, we calculate the cross-sectional covariance of x_{it} with i's first stage slope estimate. This covariance estimate is denoted $\hat{f}_t$. These serve as estimates of the latent factor realizations, f_t, by forming a weighted average of individual predictors with weights determined by first-stage slopes. The third and final pass estimates a predictive quantile regression of y_{t+h} on the time series of second-stage cross section factor estimates. Denote this final stage quantile regression coefficient as $\hat{\alpha}$.

PQR uses quantile regression in the factor estimation stage. Similar to Kelly and Pruitt's (2012) argument for partial least squares, this is done in order to extract only the relevant information f_t from cross section $\boldsymbol{x}_t$, while omitting the irrelevant factor $\boldsymbol{g}_t$. Factor latency produces an errors-in-variables problem in the first stage quantile regression, and the resulting bias introduces an additional layer of complexity in establishing PQR's consistency. To overcome this, we require the additional Assumption 4. This assumption includes finiteness of higher moments for the factors and measurement errors f_t, $\boldsymbol{g}_t$, and ε_{it}, and symmetric distributions for the target-irrelevant factor $\boldsymbol{g}_t$ and its loadings, $\boldsymbol{\psi}_i$. Importantly, we do not require additional assumptions on the quantile forecast error, η_{t+h}.

Theorem 2 (Consistency of PQR)**.** *Under Assumptions 1-4, the PQR predictor of* $\mathbb{Q}_\tau(y_{t+1}|\mathcal{I}_t) = \alpha f_t$ *is given by* $\hat{\alpha}\hat{f}_t$*, where* $\hat{f}_t$ *is the second stage factor estimate and* $\hat{\alpha}$ *is the third stage quantile regression coefficient. For each* t*, the PQR quantile forecast satisfies*

$$\hat{\alpha}\hat{f}_t - \alpha f_t \xrightarrow[N,T\to\infty]{p} 0.$$

The proof of Theorem 2 is in Appendix A.3. Simulation evidence in Appendix A.4 demonstrates that both consistency results are accurate approximations of finite sample behavior. In the next section, we refer to PCQR and PQR factor estimates ($\hat{f}_t$) as "systemic risk indexes" and evaluate their forecast performance versus individual systemic risk measures.

[21] In a preliminary step all predictors are standardized to have equal variance, as is typically done in other dimension reduction techniques such as principal components regression and partial least squares.

4.3 Empirical Evaluation of Systemic Risk Indexes

To make sure that we have a large enough cross section of systemic risk measures for the UK and EU, we construct their Multiple QR, PCQR and PQR forecasts using US systemic risk measures that are missing for these countries (for example, the default spread). Given the interconnectedness of global financial markets, these measures will be at least partly informative about financial distress in the UK and the EU as well.

Panel B of Table 4 shows that joint use of many systemic risk measures produces a high in-sample R^2 when predicting the 20^{th} percentile of future IP growth shocks in the US, UK and EU. The table shows that Multiple QR (that simultaneously includes all the systemic risk variables) works best by this metric. But Table 5 Panel B illustrates the severe overfit problem with Multiple QR. In contrast, PCQR and PQR provide significant out-of-sample performance for the lower tail of future IP growth shocks in every region and every sample split. The forecast improvement over the historical quantile is 4-10% in the UK and EU. In the US, the forecast improvement for the out-of-sample window starting in 1990 is 12-17%. When the US out-of-sample window begins in 1950 – which includes more than 240 nonoverlapping quarterly observations in the test sample – PCQR2 and PQR produce significant forecast improvements of almost 7%.[22] These results demonstrate that PCQR and PQR are powerful tools for extracting information about future macroeconomic shocks from a cross section of systemic risk measures.[23]

Figure 2 plots fitted quantiles for the sample beginning in 1970. The thin red line is the in-sample historical 20^{th} percentile. The actual shocks are plotted alongside their forecasted values based on information three months earlier (i.e., the PQR data point plotted for January 2008 is the forecast constructed using information known at the end of October 2007). NBER recessions are shown in the shaded regions. The PQR predicted quantile (the solid black line) exhibits significant variation over the last four decades, but much more so prior to the 1990's. It is interesting to note that

[22] In appendix Table A3 we drop data after 2007 and continue to find significant out-of-sample forecasts, suggesting that our results are not driven solely by the most recent financial crisis.

[23] The TED spread is only available starting in 1984. Since multiple quantile regression and PCQR require balanced panels for estimation, we drop the TED spread from the estimation of those two procedures in order to use the longer time series provided by the panel of remaining predictors. PQR is implementable with an unbalanced panel, and therefore we include the TED spread as an input to PQR.

the PQR systemic risk index predicted a large downshift in the 20^{th} percentile of IP growth after the oil price shock of the 1970's and the recessions of the early 1980's. While the 2007-2009 financial crisis led to a downward shift in the lower quantile of IP growth, this rise in downside risk is not without historical precedent.

Table 6 Panel B shows that the PQR index possesses forecasting power for the CFNAI and its subcomponents. It is significant in several cases, including for the total index where the R^2 is 7%. Table 7 Panel B shows that the PCQR2 and PQR indexes successfully forecast the 10^{th} percentile IP growth shocks out-of-sample with R^2 ranging from 5-20%. For the 10^{th} percentile of CFNAI shocks in Table 8 Panel B, the PCQR2 and PQR indexes again provide positive results, and these are significant in three out of five cases for PQR. The PQR forecast of the total CFNAI index achieves an R^2 of 9%.

Finally, we evaluate the ability of systemic risk indexes to forecast the central tendency of macro shocks. Table 9 Panel B shows that neither PCQR nor PQR provides significant out-of-sample information for the median of future IP growth.

In summary, the compendium of systemic risk measures, when taken together in PCQR and PQR algorithms, demonstrates robust predictive power for the lower tail of macroeconomic shocks. In the US, this relationship is significant when evaluated over the entire postwar period, as well as in more recent subsamples. And while systemic risk is strongly related to lower tail risk, it does not appear to affect the center of the distribution of future macroeconomic activity. This fact highlights the value of quantile regression methods, which naturally allow for asymmetric impacts of systemic risk on economic outcomes.[24]

5 Stylized Facts

Our main question in this paper is whether systemic risk measures are informative about the future distribution of macroeconomic shocks. Three central facts emerge from our analysis.

[24]We also analyze the upper tails (80^{th} percentile forecasts) of macroeconomic shocks and find no significant association with systemic risk (results untabulated).

5.1 Systemic Risk and Downside Macroeconomic Risk

First, systemic risk indexes are significantly related to macroeconomic lower tail risk, but not to the central tendency of macroeconomic variables. The preceding tables report significant predictability for the 20^{th} percentile, but find no evidence of predictability for the median. In Table 11, we formally test the hypothesis that the 20^{th} percentile and median regression coefficients are equal.[25] If the difference in coefficients (20^{th} percentile minus median) is negative, then the variable predicts a downward shift in lower tail relative to the median.[26]

Of the 19 systemic risk measures and indexes in the table, 15 are stronger predictors of downside risk than central tendency. Eleven of these differences are statistically significant at the 5% level. These results support macroeconomic models of systemic risk that feature an especially strong link between financial sector stress and the probability of a large negative shock to the real economy, as opposed to a simple downward shift in the mean.

5.2 Financial Volatility is Informative

The second stylized fact is that financial sector equity return volatility variables are the most informative individual predictors of downside macroeconomic risk.

The macroeconomic literature on uncertainty shocks, most notably Bloom (2009), argues that macroeconomic "uncertainty" (often measured by aggregate equity market volatility) is an important driver of the business cycle. Bloom shows that rises in aggregate volatility predict economic downturns.[27] Is our finding that *financial* sector volatility predicts downside macroeconomic risks merely picking up the macroeconomic uncertainty effects documented by Bloom's analysis of *aggregate* volatility? Or, instead, is the volatility of the financial sector special for understanding future macroeconomic conditions?

To explore this question, we construct two volatility variables. These are the standard deviations of value-weighted equity portfolio returns for the set of either all

[25]We sign each predictor so that it is increasing in systemic risk and normalize it to have unit variance.

[26]The t-statistics for differences in coefficients are calculated with a residual block bootstrap using block lengths of six months and 1,000 replications.

[27]Recent papers such as Baker, Bloom and Davis (2012) and Orlik and Veldkamp (2013) expand this line of research in a variety of dimensions.

financial institution stocks or all non-financial stocks.[28] We then compare quantile forecasts of IP growth shocks based on each volatility variable.

Table 12 shows that non-financial volatility possesses no significant out-of-sample predictive power for either the 20^{th} percentile or median of future macroeconomic shocks. Financial volatility is a significant predictor of both central tendency and lower tail risk, but is relatively more informative about the tail, as documented in Table 11.

We next compare the predictive content of financial and non-financial volatility for business cycle fluctuations in the statistical setting originally analyzed by Bloom (2009). That paper identifies structural shocks in a vector autoregression (VAR) via Choleski decomposition. We initially follow Bloom's variable ordering so that the role of financial volatility is not conflated with a difference in structural identification assumptions. Total market value is ordered first and controls for first-moment shocks. Bloom's aggregate market volatility measure is second and controls for economy-wide second-moment shocks. Financial volatility is ordered third and allows us to evaluate the effects of financial sector second-moment shocks above and beyond the first two variables. Additional details regarding the VAR closely follow Bloom (2009) and are available in Appendix B.5.

Figure 3 reports the impulse response function of IP growth to the structural volatility shocks.[29] Financial volatility shocks have significant effects on future industrial production even after controlling for aggregate volatility. Panel A shows that a one standard deviation shock to aggregate volatility produces a drop in log IP growth of 15-20 basis points from its HP-trend in the 3 to 6 months after impact. It rebounds to rise above trend by nearly 10 basis points within 18 months of impact. Panel B shows that a one standard deviation shock to financial volatility also causes IP to fall by more than 15 basis points in the same time frame. These estimates suggest a contractionary effect of financial volatility beyond the effect of aggregate volatility shocks.[30]

[28]The volatility variable studied in preceding quantile regressions is the average equity volatility across financial firms, an aggregation approach that is consistent with our aggregation of other firm-level measures of systemic risk. The variable described here is volatility of returns on a portfolio of stocks, which is directly comparable to the market volatility variable studied in Bloom (2009).

[29]The figure also reports bootstrapped 68% confidence bands, as in Bloom (2009).

[30]Bloom (2009) constructs an indicator variable from the volatility of aggregate stock market returns that equals one when market volatility rises by more than 1.65 standard deviations. This indicator is designed to select only extreme jumps in volatility, while we focus on the more commonly used one standard deviation impulse to the continuous volatility series. This leads us to estimate

We also find that the ordering of variables in the VAR has an important effect on estimates. We re-estimate the VAR after reversing the order of financial and aggregate volatility. This specification addresses the question: Once we have controlled for shocks to financial sector volatility, what is the effect of an aggregate volatility shock on the real economy? Figure 4, Panel A shows that after controlling for financial volatility, aggregate volatility has a small and insignificant effect on production (trend deviation of −5 basis points). In Panel B, a financial volatility shock produces a drop in IP of 20 basis points without a significant rebound thereafter. These estimates suggest that financial volatility shocks crowd out broader measures of uncertainty when forecasting real economic outcomes.

5.3 Federal Funds Policy and Systemic Risk

The third stylized fact we identify is that systemic risk indicators predict an increased probability of monetary policy easing. To show this, we examine how the government responds to fluctuations in various systemic risk measures. Historically, monetary policy is the primary tool at the disposal of policy-makers for regulating financial sector stress. We therefore test whether systemic risk indicators predict changes in the Federal Funds rate. As in our earlier analysis, we use quantile regression to forecast the median and 20^{th} percentile of rate changes. For brevity, we restrict our analysis to the three strongest predictor variables that we have studied so far: financial sector volatility, turbulence, and the PQR index of all systemic risk measures.

Results, reported in Table 13, show that in-sample forecasts of both the median and 20^{th} percentile of rate changes are highly significant. Out-of-sample, all three measures have significant predictive power for the 20^{th} percentile of rate changes. Furthermore, the out-of-sample 20^{th} percentile predictive coefficient is significantly larger than the median coefficient, indicating that these predictors are especially powerful for forecasting large policy moves.

If the government's rate reductions are effective in diffusing systemically risky conditions before they affect the real economy, then we would fail to detect a relationship between systemic risk measures and downside macroeconomic risk. But our earlier analysis shows that the lower tail of future macroeconomic shocks shifts downward amid high systemic risk, which implies that monetary policy response is

somewhat smaller impulse responses than those estimated in Bloom (2009). Using the extreme volatility indicator studied by Bloom has no qualitative effect on our results for financial volatility.

insufficient to stave off adverse macroeconomic consequences, at least in the most severe episodes.

We also use the VAR framework studied in Section 5.2 to evaluate the response of the Federal Funds rate to volatility shocks. In untabulated results, we find that a one standard deviation shock to financial volatility (with aggregate volatility preceding financial volatility in the VAR ordering) is followed by a decrease in the Federal Fund rates of around 15bp in the following year. The effect is slightly larger in magnitude than the effect of an aggregate volatility shock, and holds when the ordering of the two variables is reversed.

6 Conclusion

In this paper we quantitatively examine a large collection of recently proposed systemic risk measures. We argue that systemic risk measures should be demonstrably associated with real macroeconomic outcomes if they are to be relied upon for regulation and policy decisions. We evaluate the importance of each candidate measure by testing its ability to predict quantiles of future macroeconomic shocks. This approach is motivated by macroeconomic theories of financial frictions and a desire to flexibly model the way distributions of economic outcomes respond to shifts in systemic risk. We find that most individual measures fail to capture shifts in macroeconomic downside risk.

We then propose two procedures for aggregating information in the cross section of systemic risk measures. We motivate this approach with a factor model for the conditional quantiles of macroeconomic activity. We prove that PCQR and PQR produce consistent forecasts for the true conditional quantiles of a macroeconomic target variable. Empirically, systemic risk indexes estimated via PQR underscore the informativeness of the compendium of systemic risk measures as a whole. Our results show that, when appropriately aggregated, these measures contain robust predictive power for the distribution of macroeconomic shocks.

We present three new stylized facts. First, systemic risk measures have an especially strong association with the downside risk, as opposed to central tendency, of future macroeconomic shocks. The second is that financial sector equity volatility is particularly informative about future real activity, much more so than non-financial volatility. The third is that financial market distress tends to precede a strong monetary policy response, though this response is insufficient to fully dispel increased downside macroeconomic risk. These empirical findings can potentially serve as guideposts for macroeconomic models of systemic risk going forward.

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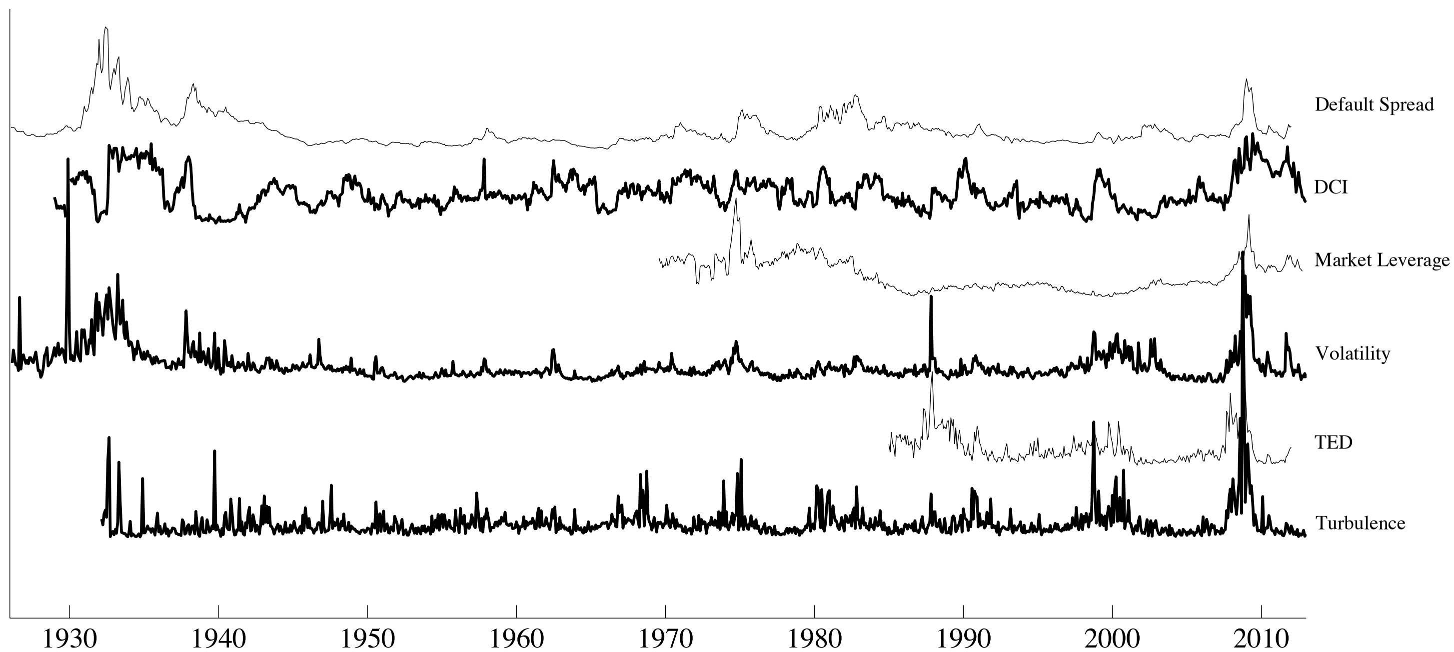

Figure 1: Systemic Risk Measures

Notes: The figure plots a subset of our panel of systemic risk measures. All measures have been standardized to have equal variance.

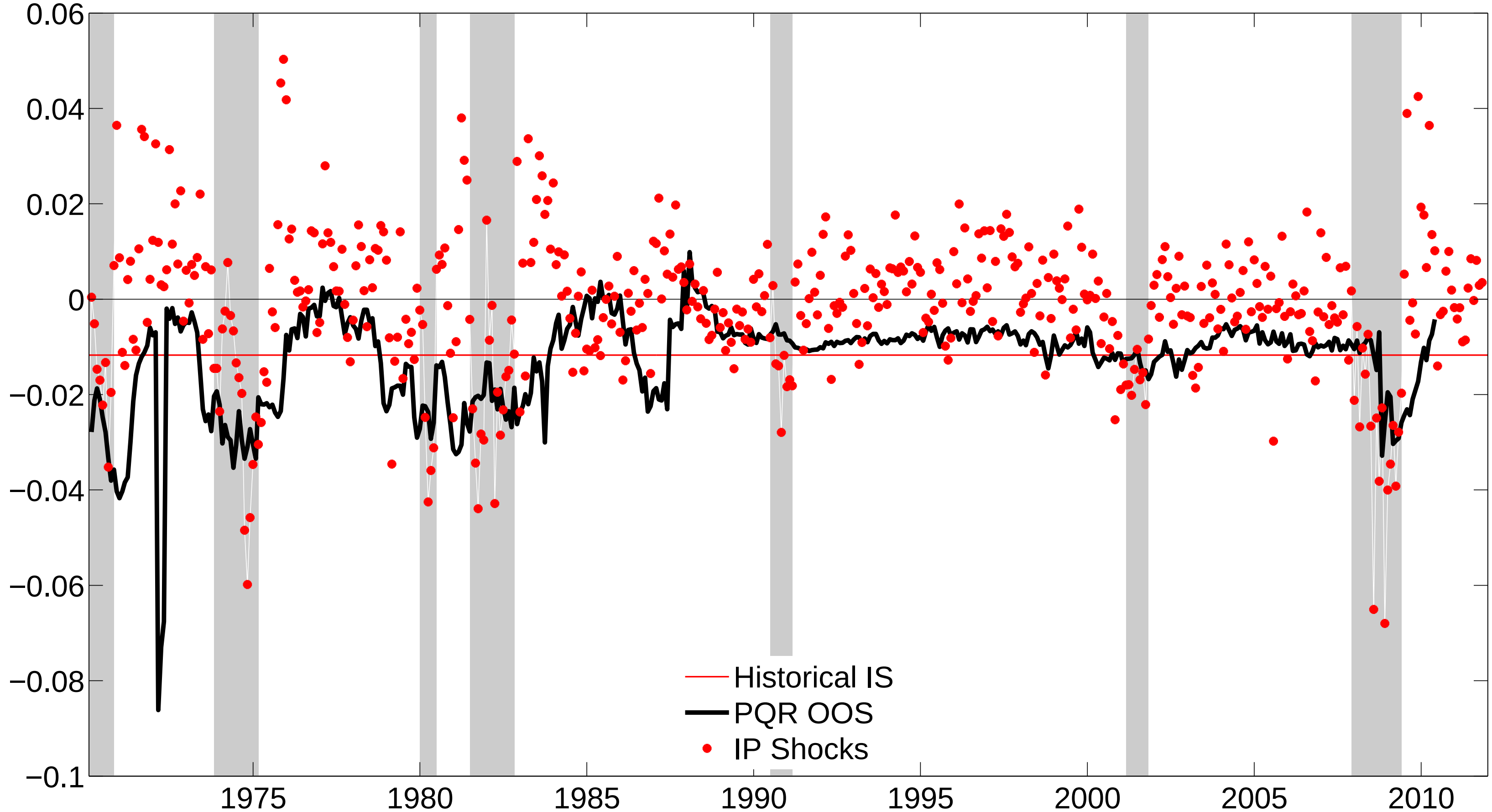

Figure 2: IP Growth Shocks and Predicted 20^{th} Percentiles

Notes: Fitted values for the 20^{th} percentile of one-quarter-ahead shocks to IP growth. "Historical IS" (the thin red line) is the in-sample (1946-2011) 20^{th} percentile of IP growth shocks and are shown as red dots. "PQR OOS" is the out-of-sample 20^{th} percentile forecast based on PQR. Timing is aligned so that the one-quarter-ahead out-of-sample forecast is aligned with the realized quarterly shock. NBER recessions are shaded.

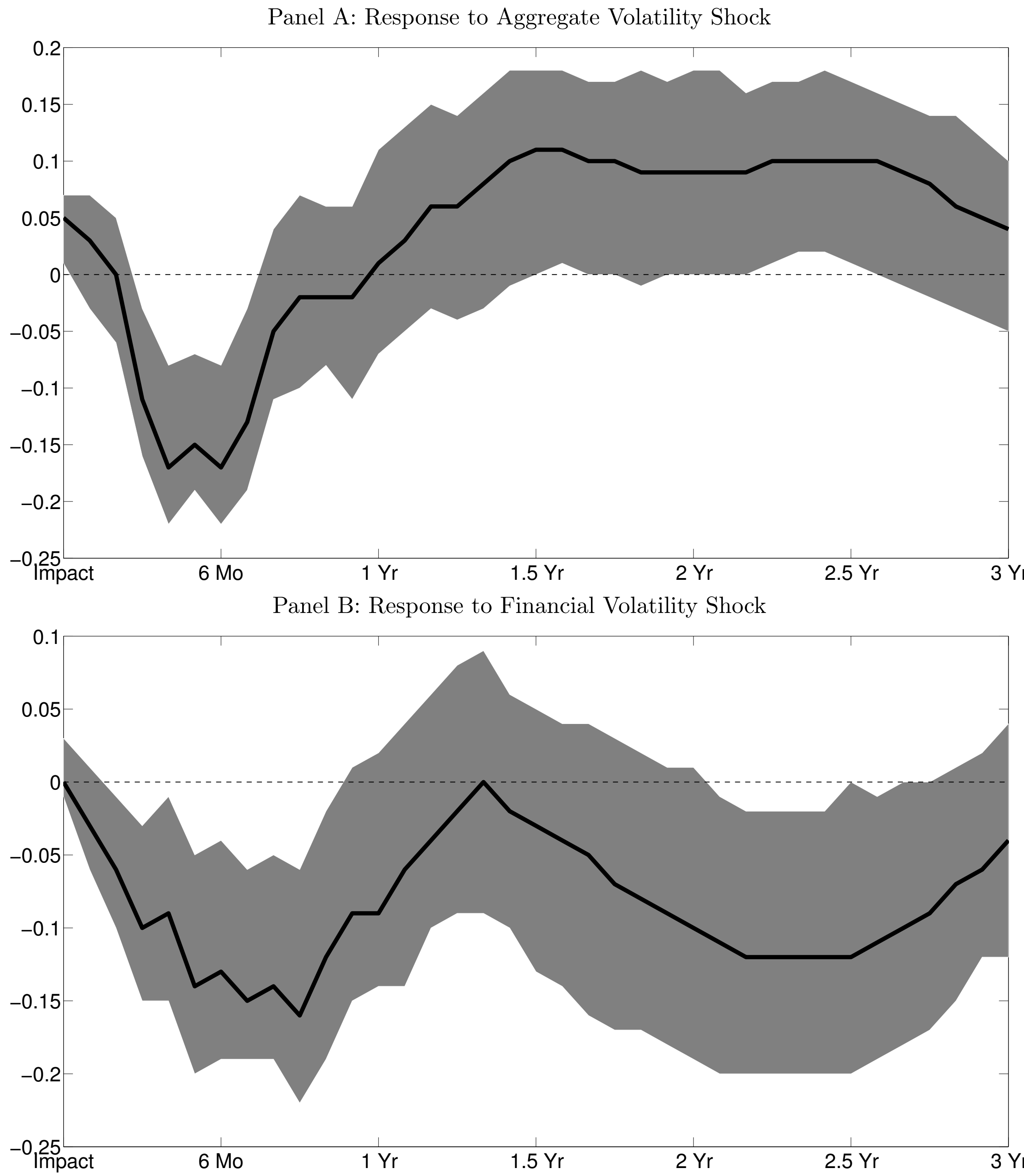

Figure 3: Impulse Responses: Market Volatility Preceding Financial Volatility in VAR

Notes: Impulse responses estimated from Bloom's (2009) VAR where total market volatility precedes financial volatility in the VAR ordering. The shaded area represents bootstrapped 68% confidence bands.

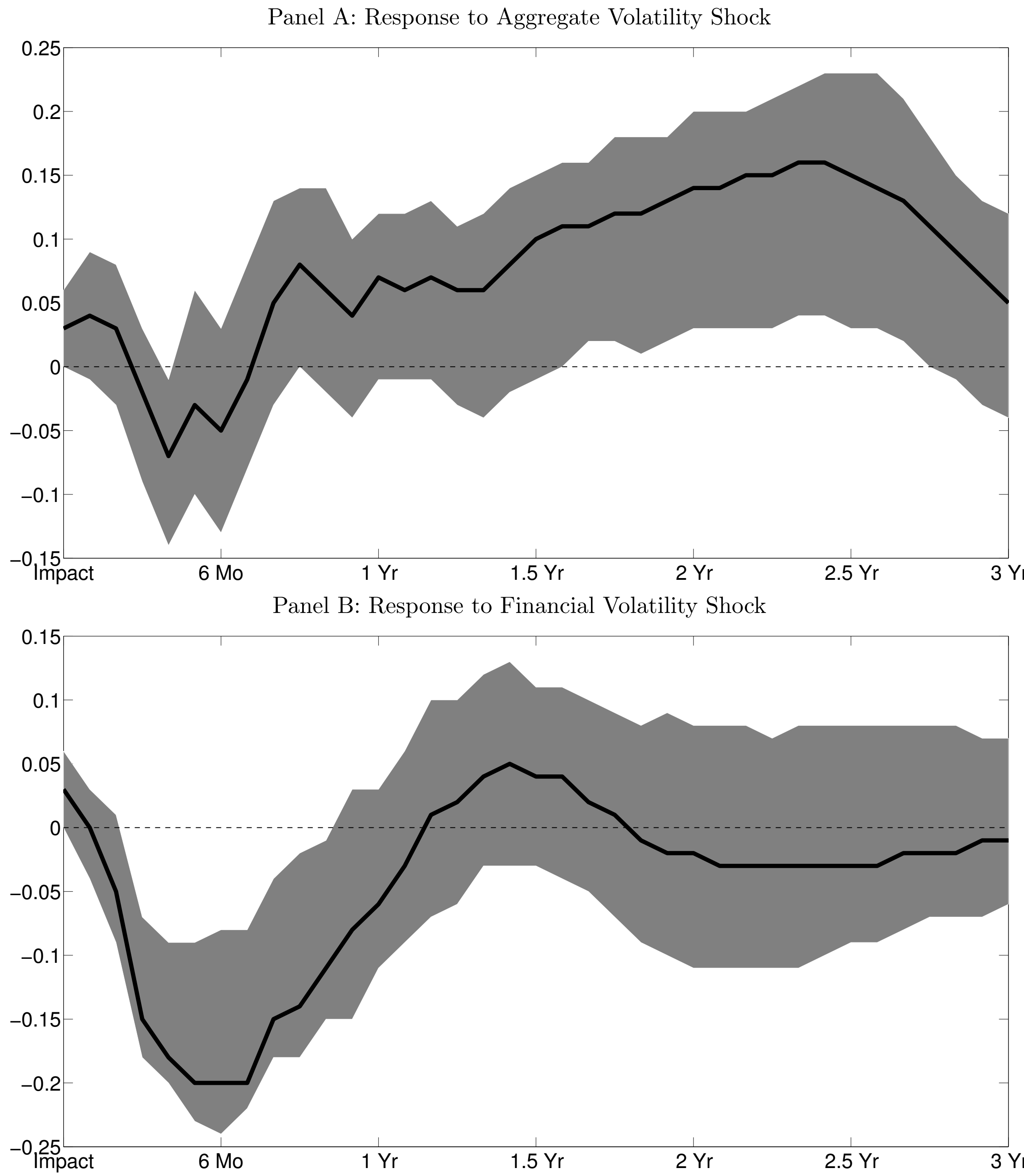

Figure 4: Impulse Responses: Financial Volatility Preceding Market Volatility in VAR

Notes: Impulse responses estimated from Bloom's (2009) VAR where financial volatility precedes total market volatility in the VAR ordering. The shaded area represents bootstrapped 68% confidence bands.

Table 1: Sample Start Dates

	US	UK	EU
Absorption	1927	1973	1973
AIM	1926	-	-
CoVaR	1927	1974	1974
ΔCoVaR	1927	1974	1974
MES	1927	1973	1973
MES-BE	1926	1973	1973
Book Lvg.	1969	-	-
DCI	1928	1975	1975
Def. Spr.	1926	-	-
ΔAbsorption	1927	1973	1973
Intl. Spillover	1963	-	-
Size Conc.	1926	1973	1973
Mkt Lvg.	1969	-	-
Real Vol.	1926	1973	1973
TED Spr.	1984	-	-
Term Spr.	1926	-	-
Turbulence	1932	1978	1978

Notes: Measures begin in the stated year and are available through 2011 with the exception of Intl. Spillover, which runs through 2009.

Table 2: Correlations Among Systemic Risk Measures

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Panel A: US																		
Absorption	(1)	1.00																
AIM	(2)	-0.03	1.00															
CoVaR	(3)	0.60	0.19	1.00														
ΔCoVaR	(4)	0.69	0.04	0.95	1.00													
MES	(5)	0.64	0.13	0.93	0.93	1.00												
MES-BE	(6)	0.35	-0.09	0.38	0.41	0.47	1.00											
Book Lvg.	(7)	-0.01	0.03	0.11	0.02	0.03	-0.20	1.00										
DCI	(8)	0.13	-0.07	0.35	0.36	0.39	0.28	0.17	1.00									
Def. Spr.	(9)	0.25	0.33	0.67	0.53	0.55	0.34	-0.09	0.24	1.00								
ΔAbsorption	(10)	-0.53	-0.01	-0.26	-0.30	-0.32	-0.15	0.06	-0.03	-0.06	1.00							
Intl. Spillover	(11)	0.42	-0.13	0.40	0.45	0.45	0.25	0.14	0.17	0.34	-0.15	1.00						
Size Conc.	(12)	0.01	0.29	0.32	0.15	0.25	-0.01	0.41	0.13	0.36	-0.03	-0.07	1.00					
Mkt Lvg.	(13)	-0.17	0.15	0.22	0.17	0.14	-0.12	0.50	0.49	0.47	0.11	0.26	0.04	1.00				
Real Vol.	(14)	0.35	0.25	0.70	0.57	0.63	0.43	0.11	0.28	0.61	0.08	0.19	0.29	0.17	1.00			
TED Spr.	(15)	0.10	0.05	0.19	0.20	0.20	0.34	-0.32	0.12	0.38	0.02	-0.16	-0.20	0.12	0.49	1.00		
Term Spr.	(16)	0.29	0.01	0.35	0.37	0.33	0.34	-0.24	0.20	0.40	-0.12	0.31	0.09	-0.08	0.14	-0.07	1.00	
Turbulence	(17)	0.11	-0.04	0.19	0.16	0.17	0.21	0.12	0.12	0.16	0.03	0.06	0.02	0.16	0.49	0.54	-0.06	1.00
Panel B: UK																		
Absorption	(1)	1.00																
CoVaR	(2)	0.57	1.00															
ΔCoVaR	(3)	0.69	0.97	1.00														
MES	(4)	0.62	0.92	0.93	1.00													
MES-BE	(5)	0.45	0.49	0.54	0.66	1.00												
DCI	(6)	0.40	0.34	0.37	0.45	0.39	1.00											
ΔAbsorption	(7)	-0.50	-0.31	-0.37	-0.35	-0.14	-0.23	1.00										
Size Conc.	(8)	0.05	0.26	0.25	0.42	0.52	0.28	-0.01	1.00									
Real Vol.	(9)	0.34	0.69	0.65	0.66	0.67	0.21	0.12	0.35	1.00								
Turbulence	(10)	0.10	0.40	0.35	0.36	0.47	0.03	0.06	0.14	0.69	1.00							
Panel C: EU																		
Absorption	(1)	1.00																
CoVaR	(2)	0.68	1.00															
ΔCoVaR	(3)	0.77	0.96	1.00														
MES	(4)	0.78	0.94	0.96	1.00													
MES-BE	(5)	0.53	0.50	0.63	0.62	1.00												
DCI	(6)	0.39	0.51	0.53	0.54	0.39	1.00											
ΔAbsorption	(7)	-0.51	-0.34	-0.38	-0.41	-0.26	-0.20	1.00										
Size Conc.	(8)	-0.02	0.19	0.17	0.08	-0.01	0.20	-0.10	1.00									
Real Vol.	(9)	0.33	0.57	0.51	0.51	0.33	0.33	0.18	-0.05	1.00								
Turbulence	(10)	0.02	0.11	0.09	0.08	0.15	0.14	0.09	-0.07	0.42	1.00							

Notes: Correlation is calculated using the longest available coinciding sample for each pair.

Table 3: Pairwise Granger Causality Tests

	US		UK		EU	
	Causes	Caused by	Causes	Caused by	Causes	Caused by
Absorption	6	3	1	1	1	6
AIM	1	2	-	-	-	-
CoVaR	8	3	4	3	3	3
ΔCoVaR	6	5	3	3	4	3
MES	5	8	3	6	2	5
MES-BE	2	10	2	8	1	6
Book Lvg.	2	2	-	-	-	-
DCI	1	7	0	6	3	0
Def. Spr.	8	3	-	-	-	-
ΔAbsorption	4	0	5	0	4	0
Intl. Spillover	0	7	-	-	-	-
Size Conc.	2	0	1	0	0	0
Mkt Lvg.	2	0	-	-	-	-
Real Vol.	9	5	6	3	6	5
TED Spr.	4	1	-	-	-	-
Term Spr.	1	8	-	-	-	-
Turbulence	6	3	6	1	5	1

Notes: For each pair of variables, we conduct two-way Granger causality tests. The table reports the number of other variables that each measure significantly Granger causes (left column) or is caused by (right column) at the 2.5% one-sided significance level (tests are for positive causation only). Tests are based on the longest available coinciding sample for each pair.

Table 4: In-Sample 20^{th} Percentile IP Growth Forecasts

	US	UK	EU
	Panel A: Individual Systemic Risk Measures		
Absorption	0.10	1.94**	7.30***
AIM	3.75***	0.56	0.63
CoVaR	3.07***	4.81***	6.04***
ΔCoVaR	1.27***	4.09***	6.30***
MES	1.53***	3.09***	5.25***
MES-BE	0.14	2.22**	5.26***
Book Lvg.	2.11**	0.83	2.12
DCI	0.14*	0.37	6.93***
Def. Spr.	2.11***	9.90***	14.84***
ΔAbsorption	0.18**	0.08	0.40
Intl. Spillover	0.55**	1.58***	2.36*
Size Conc.	0.04	6.54***	12.01***
Mkt. Lvg.	10.52***	0.76**	2.77**
Volatility	3.81***	8.73***	11.71***
TED Spr.	7.73***	3.31**	8.19***
Term Spr.	1.65**	0.07	3.07***
Turbulence	3.85***	2.42***	5.55***
	Panel B: Systemic Risk Indexes		
Multiple QR	32.30***	22.26***	37.26***
PCQR1	9.59***	9.25***	13.89***
PCQR2	20.15***	9.21***	17.27***
PQR	14.59***	10.55***	8.83***

Notes: The table reports in-sample quantile forecast R^2 (in percentage) relative to the historical quantile model. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample is 1946-2011 for US data, 1978-2011 for UK data, and 1994-2011 for EU data. Rows "Absorption" through "Turbulence" use each systemic risk measure in a univariate quantile forecast regression for the IP growth shock of the region in each column. "Multiple QR" uses all systemic risk measures jointly in a multiple quantile regression. Rows "PCQR1" through "PQR" use dimension reduction techniques on all the systemic risk measures. PCQR1 and PCQR2 use one and two principal components, respectively, in the PCQR forecasting procedure, while PQR uses a single factor. Owing to its late availability, TED Spr. is excluded from Multiple QR and PCQR calculations in the US and UK.

Table 5: Out-of-Sample 20^{th} Percentile IP Growth Forecasts

	US			UK	EU
Out-of-sample start:	1950	1970	1990	1990	2000
		Panel A: Individual Systemic Risk Measures			
Absorption	−2.80	−4.38	−3.96	0.39	5.36*
AIM	2.99**	4.01**	4.07*	−0.28	0.50*
CoVaR	1.71	2.11	1.85	6.45**	4.86**
ΔCoVaR	−0.45	−0.86	−0.97	5.42**	4.86*
MES	−0.10	0.21	0.97	2.24	2.44
MES-BE	−1.24	−0.78	−6.70	−1.59	2.84
Book Lvg.	–	–	3.87***	−2.98	0.80
DCI	−1.61	−1.75	−2.92	−5.15	5.34**
Def. Spr.	−0.29	0.69	8.60***	15.87***	11.41*
ΔAbsorption	−0.83	−0.10	−0.27	0.11	0.05
Intl. Spillover	–	0.34	1.41	−0.15	−1.32
Size Conc.	−2.48	−7.37	−3.59	7.06**	10.93***
Mkt. Lvg.	–	–	12.70***	−3.63	−0.57
Volatility	3.27**	6.19**	8.03*	8.35**	6.83
TED Spr.	–	–	10.18***	−1.06	1.06
Term Spr.	0.32	2.13	1.14	−2.70	1.23
Turbulence	3.50***	6.93***	12.78***	−3.62	−0.38
		Panel B: Systemic Risk Indexes			
Multiple QR	−23.66	−18.52	15.21***	−14.39	−3.25
PCQR1	0.68	0.13	1.61	6.01**	12.03**
PCQR2	6.47***	10.52***	16.67***	3.38	9.33*
PQR	6.58***	10.82***	12.39***	4.49*	5.14*

Notes: The table reports out-of-sample quantile forecast R^2 (in percentage) relative to the historical quantile model. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample is 1946-2011 for US data, 1978-2011 for UK data and 1994-2011 for EU data. Out-of-sample start date is noted for each column. Rows "Absorption" through "Turbulence" use each systemic risk measure in a univariate quantile forecast regression for IP growth rate shocks. "Multiple QR" uses all systemic risk measures jointly in a multiple quantile regression. Rows "PCQR1" through "PQR" use dimension reduction techniques on all the systemic risk measures. PCQR1 and PCQR2 use one and two principal components, respectively, in the PCQR forecasting procedure, while PQR uses a single factor. Owing to its late availability, TED Spr. is excluded from Multiple QR and PCQR calculations in the US and UK. "–" indicates insufficient data for estimation in a given sample.

Table 6: Out-of-Sample 20^{th} Percentile CFNAI Shock Forecasts

	Total	PH	PI	SOI	EUH
	Panel A: Individual Systemic Risk Measures				
Absorption	−4.58	−1.85	−2.66	−3.11	−3.00
AIM	−3.42	−2.60	−2.69	−3.44	−1.67
CoVaR	−1.82	−2.98	−2.83	−3.27	−0.94
ΔCoVaR	−4.55	−2.59	−4.11	−4.49	−4.31
MES	−3.62	−2.51	−4.81	−3.64	−3.09
MES-BE	−2.25	−1.68	−0.60	−2.70	−2.50
Book Lvg.	0.49	−2.19	1.36	−0.47	1.19
DCI	−2.14	−0.67	−2.28	−3.50	−2.42
Def. Spr.	−0.38	−3.88	−0.84	−3.15	−3.19
ΔAbsorption	−0.37	−1.92	1.16	−0.53	0.59
Intl. Spillover	−2.52	−3.62	−0.94	−1.78	−2.38
Size Conc.	−1.84	−1.66	−0.60	−2.77	−0.17
Mkt. Lvg.	4.26*	−0.78	4.14*	5.70**	4.14*
Volatility	1.65	−0.07	1.00	2.97	2.14
Term Spr.	3.03	0.64	3.32	2.64	2.36
Turbulence	7.37**	4.82**	7.97***	8.40***	4.46*
	Panel B: Systemic Risk Indexes				
Multiple QR	−36.74	−47.07	−52.06	−20.00	−54.18
PCQR1	−1.07	−0.73	−1.96	−2.06	−0.24
PCQR2	0.89	−2.44	0.20	−0.65	0.28
PQR	7.09**	2.16	5.36*	9.72***	2.15

Notes: The table reports out-of-sample quantile forecast R^2 (in percentage) relative to the historical quantile model. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample is 1967-2011. Out-of-sample start date is 1975. Rows "Absorption" through "Turbulence" use each systemic risk measure in a univariate quantile forecast regression for the CFNAI index or sub-index in each column. "Multiple QR" uses all systemic risk measures jointly in a multiple quantile regression. Rows "PCQR1" through "PQR" use dimension reduction techniques on all the systemic risk measures. PCQR1 and PCQR2 use one and two principal components, respectively, in the PCQR forecasting procedure, while PQR uses a single factor. Owing to its late availability, TED Spr. is excluded.

Table 7: 10^{th} Percentile IP Growth Forecasts

	In-Sample	Out-of-Sample		
Out-of-sample start:		1950	1970	1990
	Panel A: Individual Systemic Risk Measures			
Absorption	0.14	−2.81	−5.08	−9.54
AIM	6.97**	6.30***	7.32**	6.70*
CoVaR	2.47**	−0.02	1.59	−0.91
ΔCoVaR	1.42	−0.80	0.50	−1.44
MES	1.51*	−1.50	1.53	0.39
MES-BE	0.07	−2.52	−3.60	−16.31
Book Lvg.	4.07***	–	–	7.30***
DCI	1.45	0.56	0.48	4.63*
Def. Spr.	1.78*	0.66	1.00	6.82***
ΔAbsorption	0.16	−1.89	−0.51	−0.35
Intl. Spillover	2.15**	–	4.51	8.73***
Size Conc.	0.79	−2.26	−8.23	−3.50
Mkt. Lvg.	17.87***	–	–	20.93***
Volatility	3.63**	2.95*	5.49**	4.98
TED Spr.	12.88***	–	–	12.23***
Term Spr.	2.26**	1.11	2.46	−2.02
Turbulence	3.77**	2.27	4.17*	12.50**
	Panel B: Systemic Risk Indexes			
Multiple QR	38.86***	−54.86	−33.99	17.14**
PCQR1	7.77*	−0.41	3.60*	−0.81
PCQR2	27.28***	7.19***	16.20***	19.38***
PQR	12.96***	5.19*	11.36***	10.28**

Notes: The table reports quantile forecast R^2 (in percentage) relative to the historical quantile model. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample is 1946-2011. In-sample statistics are in column one. The out-of-sample start is noted for columns two through four. Rows "Absorption" through "Turbulence" use each systemic risk measure in a univariate quantile forecast regression for US IP growth rate shocks. "Multiple QR" uses all systemic risk measures jointly in a multiple quantile regression. Rows "PCQR1" through "PQR" use dimension reduction techniques on all the systemic risk measures. PCQR1 and PCQR2 use one and two principal components, respectively, in the PCQR forecasting procedure, while PQR uses a single factor. Owing to its late availability, TED Spr. is excluded from Multiple QR and PCQR calculations. "–" indicates insufficient data for estimation in a given sample.

Table 8: Out-of-Sample 10^{th} Percentile CFNAI Shock Forecasts

	Total	PH	PI	SOI	EUH
	Panel A: Individual Systemic Risk Measures				
Absorption	−3.64	−7.62	−6.04	−4.90	−4.92
AIM	−0.93	−7.86	−3.29	1.26	−4.48
CoVaR	−1.58	−4.93	−1.57	2.20	−1.05
ΔCoVaR	−2.99	−4.52	−4.42	−1.47	−4.38
MES	−3.78	−5.54	−6.81	−2.89	−4.02
MES-BE	−4.29	−2.83	−3.40	−3.29	−3.64
Book Lvg.	2.74*	−4.35	0.60	2.62	4.31***
DCI	−7.13	−5.47	−3.85	−6.72	−4.31
Def. Spr.	−2.99	−4.79	−2.53	−4.51	−1.47
ΔAbsorption	1.11	−1.77	−0.89	0.95	0.20
Intl. Spillover	−5.42	−5.63	−4.09	−3.68	−2.18
Size Conc.	−3.50	−1.86	−2.46	−3.32	−0.44
Mkt. Lvg.	11.48***	−1.71	7.58*	13.85***	8.83**
Volatility	6.65	0.78	3.68	6.11*	4.35
Term Spr.	1.31	−2.18	1.61	1.52	−0.82
Turbulence	11.76***	4.07	12.77**	9.48***	8.77**
	Panel B: Systemic Risk Indexes				
Multiple QR	−68.49	−85.59	−95.11	−41.80	−61.78
PCQR1	−3.84	−0.70	−4.45	0.35	0.37
PCQR2	0.03	0.07	1.70	3.21	0.30
PQR	9.07**	2.20	9.50**	8.84**	6.55

Notes: The table reports out-of-sample quantile forecast R^2 (in percentage) relative to the historical quantile model. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample is 1967-2011. Out-of-sample start date is 1975. Rows "Absorption" through "Turbulence" use each systemic risk measure in a univariate quantile forecast regression for the CFNAI index or sub-index in each column. "Multiple QR" uses all systemic risk measures jointly in a multiple quantile regression. Rows "PCQR1" through "PQR" use dimension reduction techniques on all the systemic risk measures. PCQR1 and PCQR2 use one and two principal components, respectively, in the PCQR forecasting procedure, while PQR uses a single factor. Owing to its late availability, TED Spr. is excluded.

Table 9: Out-of-Sample Median IP Growth Shock Forecasts

	US			UK	EU
Out-of-sample start:	1950	1970	1990	1990	2000
	Panel A: Individual Systemic Risk Measures				
Absorption	−0.58	1.63*	1.55	−1.17	1.44
AIM	0.07	−1.68	0.15*	−0.30	−0.01
CoVaR	0.33	−1.26	0.72	−1.60	1.52
ΔCoVaR	−0.26	−1.59	−0.03	−0.97	0.69
MES	−0.23	−1.46	−0.80	−1.70	−0.05
MES-BE	−1.17	−0.44	−0.39	3.63**	−0.41
Book Lvg.	–	–	1.19	3.05***	−2.05
DCI	−1.41	−1.09	−1.00	−1.00	0.54
Def. Spr.	−0.59	0.48	4.83***	0.80	−2.47
ΔAbsorption	−0.72	−0.44	−0.30	−0.22	−0.08
Intl. Spillover	–	−1.46	−0.65	−2.15	−0.27
Size Conc.	−2.61	−1.60	−3.43	3.54**	3.35**
Mkt. Lvg.	–	–	2.77*	−1.72	−4.69
Volatility	1.21	2.46	4.49*	1.76*	−1.34
TED Spr.	–	–	2.03**	−2.44	−1.77
Term Spr.	0.08	0.21	−0.35	−0.37	−1.68
Turbulence	1.37**	2.60**	4.49**	0.23	−0.47
	Panel B: Systemic Risk Indexes				
Multiple QR	−19.78	−19.17	−0.35	−11.30	−15.92
PCQR1	−0.36	−1.99	1.36	1.24	−0.66
PCQR2	1.00	−0.80	2.31	1.00	−2.54
PQR	−1.64	−4.39	3.64*	−1.76	−9.73

Notes: The table reports out-of-sample quantile forecast R^2 (in percentage) relative to the historical quantile model. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample is 1946-2011 for US data, 1978-2011 for UK data and 1994-2011 for EU data. Out-of-sample start date is noted for each column. Rows "Absorption" through "Turbulence" use each systemic risk measure in a univariate quantile forecast regression for IP growth rate shocks. "Multiple QR" uses all systemic risk measures jointly in a multiple quantile regression. Rows "PCQR1" through "PQR" use dimension reduction techniques on all the systemic risk measures. PCQR1 and PCQR2 use one and two principal components, respectively, in the PCQR forecasting procedure, while PQR uses a single factor. Owing to its late availability, TED Spr. is excluded from Multiple QR and PCQR calculations in the US and UK. "–" indicates insufficient data for estimation in a given sample.

Table 10: Estimators

Principal Components Quantile Regression (PCQR)	
Factor Stage:	Estimate $\hat{\boldsymbol{F}}_t$ by $(\boldsymbol{\Lambda}'\boldsymbol{\Lambda})^{-1}\boldsymbol{\Lambda}'\boldsymbol{x}_t$ for $\boldsymbol{\Lambda}$ the K eigenvectors associated with the K largest eigenvalues of $\sum_{t=1}^{T}\boldsymbol{x}_t\boldsymbol{x}_t'$
Predictor Stage:	Time series quantile regression of y_{t+h} on a constant and $\hat{\boldsymbol{F}}_t$
Partial Quantile Regression (PQR)	
Factor Stage:	1. Time series quantile regression of y_{t+h} on a constant and x_{it} to get slope estimate $\hat{\phi}_i$ 2. Cross-section covariance of x_{it} and $\hat{\phi}_i$ for each t to get factor estimate $\hat{f}_t$
Predictor Stage:	Time series quantile regression of y_{t+h} on a constant and $\hat{f}_t$

Notes: The predictors $\boldsymbol{x}_t$ are each time-series standardized. All quantile regressions and orthogonal quantile regressions are run for quantile τ.

Table 11: Difference in Coefficients, Median versus 20^{th} Percentile

	Median	20^{th} Pctl.	Difference	t
Absorption	−0.0021	−0.0010	0.0012	1.88
AIM	0.0003	−0.0072	−0.0075	−11.84
CoVaR	−0.0030	−0.0048	−0.0019	−2.89
ΔCoVaR	−0.0024	−0.0031	−0.0007	−1.02
MES	−0.0024	−0.0040	−0.0016	−2.54
MES-BE	−0.0003	0.0016	0.0019	3.01
Book Lvg.	−0.0014	−0.0023	−0.0009	−1.36
DCI	0.0001	−0.0014	−0.0016	−2.47
Def. Spr.	−0.0036	−0.0033	0.0003	0.52
ΔAbsorption	0.0004	−0.0018	−0.0023	−3.57
Intl. Spillover	0.0000	−0.0019	−0.0019	−2.87
Size Conc.	0.0007	0.0004	−0.0002	−0.33
Mkt. Lvg.	−0.0028	−0.0071	−0.0042	−6.48
Volatility	−0.0041	−0.0054	−0.0014	−2.13
TED Spr.	−0.0026	−0.0057	−0.0031	−4.65
Term Spr.	0.0017	0.0038	0.0021	3.34
Turbulence	−0.0040	−0.0060	−0.0020	−3.16
PCQR1	−0.0038	−0.0046	−0.0008	−1.28
PQR	−0.0037	−0.0052	−0.0015	−2.32

Notes: In the first two columns, the table reports quarterly quantile regression coefficients for IP growth shocks at the 50^{th} and 20^{th} percentiles. In each case, the predictor variable has been standardized to have unit variance. The third column is the difference between the 20^{th} and 50^{th} percentile coefficients. The last column reports t-statistics for the difference in coefficients. Sample is 1946-2011, or the longest span for which the predictor is available.

Table 12: IP Growth Quantile Forecasts: Financial versus Non-financial Volatility

	In-Sample	Out-of-Sample		
Out-of-sample start:		1950	1970	1990
		Panel A: 20^{th} Percentile		
Financial Volatility	3.43^{***}	2.64^{**}	5.77^{***}	12.18^{***}
Non-financial Volatility	1.37	-0.94	0.02	1.56
		Panel B: Median		
Financial Volatility	2.43^{***}	1.73^{*}	3.78^{**}	8.00^{**}
Non-financial Volatility	1.26^{**}	0.37	1.09	2.55^{*}

Notes: The table reports out-of-sample quantile forecast R^2 (in percentage) relative to the historical quantile model. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample is 1946-2011. Rows use either financial or non-financial volatility (calculated as the average individual equity return volatility for stocks in each sector) in a quantile forecasting regression for IP growth. Panel A reports 20^{th} percentile forecasts and Panel B reports median forecasts.

Table 13: Federal Funds Rate Forecasts

	Median	20^{th} Pctl.
	Panel A: In-Sample	
Volatility	2.60^{***}	5.55^{***}
Turbulence	2.33^{***}	4.20^{***}
PQR	2.29^{***}	14.45^{***}
	Panel B: Out-of-Sample	
Volatility	0.43	4.46^{*}
Turbulence	1.33^{**}	3.08^{*}
PQR	-8.97	6.60^{*}

Notes: The table reports out-of-sample quantile forecast R^2 (in percentage) relative to the historical quantile model. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample is 1955-2011. Out-of-sample begins 1960. Rows "Volatility" and "Turbulence" report univariate quantile forecast regressions on quarterly shocks to the Federal Funds rate. Row "PQR" uses a single factor estimated from all systemic risk measures.

Appendices

A Theoretical Appendix

A.1 Assumptions

Assumption 1. *Let $\mathcal{I}_t$ denote the information set at time t and $\mathbb{Q}_\tau(y_{t+h}|\mathcal{I}_t)$ denote the time-t conditional $\tau-$quantile of y_{t+h}. Let f_t be 1×1 and $\boldsymbol{g}_t$ be $K_g \times 1$ with $K = 1 + K_g$, $\boldsymbol{F}_t \equiv (f_t, \boldsymbol{g}_t')'$, and $\boldsymbol{x}_t$ be $N \times 1$, for $t = 1, \dots, T$. Then*

1. $\mathbb{Q}_\tau(y_{t+h}|\mathcal{I}_t) = \mathbb{Q}_\tau(y_{t+h}|\boldsymbol{f}_t) = \alpha_0 + \boldsymbol{\alpha}(\tau)'\boldsymbol{F}_t = \alpha_0 + \alpha(\tau)f_t$
2. $y_{t+h} = \alpha_0 + \alpha(\tau)f_t + \eta_{t+h}(\tau)$
3. $\boldsymbol{x}_t = \boldsymbol{\lambda}_0 + \boldsymbol{\phi} f_t + \boldsymbol{\Psi}\boldsymbol{g}_t + \boldsymbol{\varepsilon}_t = \boldsymbol{\lambda}_0 + \boldsymbol{\Lambda}\boldsymbol{F}_t + \boldsymbol{\varepsilon}_t$

where $\boldsymbol{\Lambda} \equiv (\boldsymbol{\lambda}_1, \dots, \boldsymbol{\lambda}_N)'$.

Assumption 2. *Let $||\boldsymbol{A}|| = (tr(\boldsymbol{A}'\boldsymbol{A}))^{1/2}$ denote the norm of matrix $\boldsymbol{A}$, and M be some positive finite scalar.*

1. *The variables $\{\Lambda_i\}$, $\{\boldsymbol{F}_t\}$, $\{\varepsilon_{it}\}$ and $\{\eta_{it}\}$ are independent groups.*
2. $\mathbb{E}||\boldsymbol{F}_t||^4 \leq M < \infty$ *and* $\frac{1}{T}\sum_{t=1}^{T} \boldsymbol{F}_t\boldsymbol{F}_t' \to \boldsymbol{\Sigma}_F$ *or some $K \times K$ positive definite matrix* $\boldsymbol{\Sigma}_F \equiv \begin{bmatrix} \Sigma_f & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma}_g \end{bmatrix}$.
3. $||\lambda_i|| \leq \bar{\lambda} < \infty$ *and* $||\boldsymbol{\Lambda}'\boldsymbol{\Lambda}/N - \boldsymbol{\Sigma}_\Lambda|| \to 0$ *for some $K \times K$ positive definite matrix* $\boldsymbol{\Sigma}_\Lambda \equiv \begin{bmatrix} \Sigma_\phi & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma}_\psi \end{bmatrix}$.
4. *For all (i, t),* $\mathbb{E}(\varepsilon_{it}) = 0, \mathbb{E}|\varepsilon_{it}|^8 \leq M$
5. *There exist* $\mathbb{E}(\varepsilon_{it}\varepsilon_{js}) = \sigma_{ij,ts}$ *and* $|\sigma_{ij,ts}| < \bar{\sigma}_{ij}$ *for all (t, s), and* $|\sigma_{ij,ts}| \leq \tau_{ts}$ *for all (i, j) such that* $\frac{1}{N}\sum_{i,j=1}^{N} \bar{\sigma}_{ij} \leq M$, $\frac{1}{T}\sum_{t,s=1}^{T} \tau_{ts} \leq M$, *and* $\frac{1}{NT}\sum_{i,j,s,t=1} |\sigma_{ij,ts}| \leq M$
6. *For every (t, s),* $\mathbb{E}|\frac{1}{\sqrt{N}}\sum_{i=1}^{N}[\varepsilon_{is}\varepsilon_{it} - \mathbb{E}(\varepsilon_{is}\varepsilon_{it})]|^4 \leq M$

Assumption 3. *Let m, M be positive finite scalars. For each $\tau \in (0, 1)$ the shock $\eta_{t+h}(\tau)$ has conditional density $\pi_\tau(\cdot|\mathcal{I}_t) \equiv \pi_{\tau t}$ and is such that*

1. *$\pi_{\tau t}$ is everywhere continuous*
2. *$m \leq \pi_{\tau t} \leq M$ for all t*
3. *$\pi_{\tau t}$ satisfies the Lipschitz condition $|\pi_{\tau t}(\kappa_1) - \pi_{\tau t}(\kappa_2)| \leq M|\kappa_1 - \kappa_2|$ for all t*

Assumption 4. *Let M be a positive finite scalar.*

1. *In addition to Assumption 2.1, $\{f_t\}$ is independent of $\{\boldsymbol{g}_t\}$ and $\{\phi_i\}$ is independent of $\{\boldsymbol{\psi}_i\}$*
2. *$\{\varepsilon_{it}\}$ are i.i.d.*
3. *$\lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\phi_i} < M$.*
4. *$\mathbb{E}(f_t^n)$, $\mathbb{E}(\boldsymbol{g}_t^n)$ and $\mathbb{E}(\boldsymbol{\varepsilon}_t^n)$ exist and are finite for all n.*
5. *$\{\boldsymbol{g}_t\}$ and $\{\boldsymbol{\psi}_i\}$ have symmetric distributions.*

Proof Outline Assumptions 1 and 2 are the same as those in Bai and Ng's (2006) work on principal components factor estimates in OLS regressions. Assumption 3 is sufficient to show that quantile regression is consistent in a time series setting. Assumption 4 strengthens some moment and independence conditions of Assumption 2 and additionally imposes conditions on the distributions of ϕ_i, $\boldsymbol{\psi}_i$ and $\boldsymbol{g}_u$.

Our approach views the latent factor structure among systemic risk measures as an errors-in-variables quantile regression problem. To address this, we rely heavily on mis-specified quantile regression results from Angrist, Chernozhukov and Fernandez-Val (2006, ACF hereafter) to express biases that arise in various stages of the PCQR and PQR procedures.[31]

For PCQR, Bai (2003) tells us that the principal component factor estimates converge to a rotation of the true factor space at rate $\min(\sqrt{N}, T)$ under Assumptions 1 and 2. We write an infeasible second stage quantile regression of y_{t+h} on the factor estimate and its deviation from the true factor. The probability limit of this infeasible quantile regression follows by Assumption 3 and allows for an ACF bias representation of the feasible quantile regression of y_{t+h} on the factor estimate alone. This allows us to show that the fitted conditional quantile from the second stage quantile regression is consistent for the true conditional quantile for N, T large.

The proof for PQR looks similar. The main difference is PQR's latent factor estimator, which is not based on PCA. PQR's first stage quantile regressions of y_{t+h} on x_{it} involves an errors-in-variables bias that remains in the large N and T limit. We write an infeasible first stage quantile regression of y_{t+h} on x_{it} and the two components of its measurement error $(\boldsymbol{g}_t, \varepsilon_{it})$. For each i, the probability limit of this infeasible quantile regression follows by Assumptions 1-3 and allows for an ACF bias representation of the feasible quantile regression regression of y_{t+h} on x_{it} alone. For each t, the factor estimate comes from cross-sectional covariance of x_{it} with the mis-measured first-stage coefficients. This converges to a scalar times the true factor at

[31] The results of Bai (2003) and Bai and Ng (2008a) can be used to establish the consistency of the PCQR. We provide an alternative derivation in order to closely connect the proofs of both PCQR and PQR.

rate $\min(\sqrt{N}, \sqrt{T})$ under Assumption 4. This results makes use of a fact about the covariance of a symmetrically-distributed random variable with a rational function of its square, which is proved in Lemma 1. The third stage quantile regression using this factor is consistent for the true conditional quantile in the joint N, T limit.

A.2 Proof of Theorem 1

Proof. Let $\hat{\boldsymbol{F}}_t$ be given by the first K principal components of $\boldsymbol{x}_t$. Bai (2003) Theorem 1 implies that for each t, $\hat{\boldsymbol{F}}_t - \boldsymbol{H}\boldsymbol{F}_t$ is at least $O_p(\delta_{NT}^{-1})$, where $\delta_{NT} \equiv \min(\sqrt{N}, \sqrt{T})$, $\boldsymbol{H} = \tilde{\boldsymbol{V}}^{-1}(\tilde{\boldsymbol{F}}'\boldsymbol{F}/T)(\boldsymbol{\Lambda}'\boldsymbol{\Lambda}/N)$, $\tilde{\boldsymbol{F}} \equiv (\tilde{\boldsymbol{F}}_1, \ldots, \tilde{\boldsymbol{F}}_T)$ is the matrix of K eigenvectors (multiplied by $\sqrt{T}$) associated with the K largest eigenvalues of $\boldsymbol{X}\boldsymbol{X}'/(TN)$ in decreasing order, and $\tilde{\boldsymbol{V}}$ is the $K \times K$ diagonal matrix of the K largest eigenvalues.[32]

The second stage quantile regression coefficient is given by

$$(\hat{\alpha}_0, \hat{\boldsymbol{\alpha}}) = arg \min_{\alpha_0, \boldsymbol{\alpha}} \frac{1}{T} \sum_{t=1}^{T} \rho_\tau(y_{t+h} - \alpha_0 - \boldsymbol{\alpha}'\hat{\boldsymbol{F}}_t).$$

Consider an infeasible regression of y_{t+h} on the PCA factor estimate $\hat{\boldsymbol{F}}_t$ as well as the factor estimation error $\hat{\boldsymbol{F}}_t - \boldsymbol{H}\boldsymbol{F}_t$ (for given N and T). Because $\boldsymbol{F}_t$ linearly depends on $(\hat{\boldsymbol{F}}_t, \hat{\boldsymbol{F}}_t - \boldsymbol{H}\boldsymbol{F}_t)$, this regression nests the correctly specified quantile forecast regression. By White (1994) Corollary 5.12[33] and the equivariance properties of quantile regression we have that the infeasible regression coefficients

$$(\dot{\alpha}_0, \dot{\boldsymbol{\alpha}}, \dot{\boldsymbol{\alpha}}_1) = arg \min_{\alpha_0, \boldsymbol{\alpha}_1, \boldsymbol{\alpha}} \frac{1}{T} \sum_{t=1}^{T} \rho_\tau(y_{t+h} - \alpha_0 - \boldsymbol{\alpha}'\hat{\boldsymbol{F}}_t - \boldsymbol{\alpha}_1'(\hat{\boldsymbol{F}}_t - \boldsymbol{H}\boldsymbol{F}_t)),$$

are such that $\dot{\boldsymbol{\alpha}}$ satisfies

$$\sqrt{T}(\dot{\boldsymbol{\alpha}} - \boldsymbol{\alpha}'\boldsymbol{H}^{-1}) \xrightarrow[T\to\infty]{d} N(\boldsymbol{0}, \boldsymbol{\Sigma}_{\dot{\boldsymbol{\alpha}}}).$$

Next, ACF (2006) Theorem 1 implies that

$$\hat{\boldsymbol{\alpha}} = \dot{\boldsymbol{\alpha}} + \left(\sum_{u=1}^{T} w_u \hat{\boldsymbol{F}}_u \hat{\boldsymbol{F}}_u'\right)^{-1} \left(\sum_{u=1}^{T} w_u \hat{\boldsymbol{F}}_u \dot{\boldsymbol{\alpha}}_1'(\hat{\boldsymbol{F}}_u - \boldsymbol{H}\boldsymbol{F}_u)\right) \tag{A1}$$

where they derive the weight function $w_t = \frac{1}{2}\int_0^1 \pi_\tau\left(v\left[\hat{\boldsymbol{\alpha}}'\hat{\boldsymbol{F}}_t - \alpha f_t\right]\right) dv$.

[32] Bai (2003) shows that $\hat{\boldsymbol{F}}_t - \boldsymbol{H}\boldsymbol{F}_t$ is $O_p(\min(\sqrt{N}, T)^{-1})$, which is at least as fast a rate of convergence as $O_p(\min(\sqrt{N}, \sqrt{T})^{-1})$.

[33] Note that our assumptions satisfy Engle and Manganelli's (2004) assumptions C0-C7 and AN1-AN4.

Next, we rewrite the forecast error as

$$\hat{\boldsymbol{\alpha}}'\hat{\boldsymbol{F}}_t - \boldsymbol{\alpha}'\boldsymbol{F}_t = \hat{\boldsymbol{\alpha}}'(\hat{\boldsymbol{F}}_t - \boldsymbol{H}\boldsymbol{F}_t) + (\hat{\boldsymbol{\alpha}}' - \boldsymbol{\alpha}'\boldsymbol{H}^{-1})\boldsymbol{H}\boldsymbol{F}_t. \tag{A2}$$

As stated above, the first term of (A2) is no bigger than $O_p(\delta_{NT}^{-1})$. To evaluate the second term, use (A1) to obtain

$$(\hat{\boldsymbol{\alpha}}' - \boldsymbol{\alpha}'\boldsymbol{H}^{-1}) = (\dot{\boldsymbol{\alpha}}' - \boldsymbol{\alpha}'\boldsymbol{H}^{-1}) + \left(\frac{1}{T}\sum_{u=1}^{T} w_u \hat{\boldsymbol{F}}_u \hat{\boldsymbol{F}}'_u\right)^{-1} \left(\frac{1}{T}\sum_{u=1}^{T} w_u \hat{\boldsymbol{F}}_u \dot{\boldsymbol{\alpha}}'_1(\hat{\boldsymbol{F}}_u - \boldsymbol{H}\boldsymbol{F}_u)\right). \tag{A3}$$

The first term on the right-hand side is $O_p(T^{-1/2})$, as stated above. Use $\hat{\boldsymbol{F}}_u \equiv \hat{\boldsymbol{F}}_u - \boldsymbol{H}\boldsymbol{F}_u + \boldsymbol{H}\boldsymbol{F}_u$ to rewrite the numerator of the second term on the right-hand side

$$\begin{aligned}
&\frac{1}{T}\sum_{u=1}^{T} w_u \hat{\boldsymbol{F}}_u \dot{\boldsymbol{\alpha}}'_1(\hat{\boldsymbol{F}}_u - \boldsymbol{H}\boldsymbol{F}_u) \\
&= \delta_{NT}^{-2}\frac{1}{T}\sum_{u=1}^{T} w_t \delta_{NT}(\hat{\boldsymbol{F}}_u - \boldsymbol{H}\boldsymbol{F}_u)\dot{\boldsymbol{\alpha}}'_1 \delta_{NT}(\hat{\boldsymbol{F}}_u - \boldsymbol{H}\boldsymbol{F}_u) + \delta_{NT}^{-1}\frac{1}{T}\sum_{u=1}^{T} w_t \boldsymbol{H}\boldsymbol{F}_u \dot{\boldsymbol{\alpha}}'_1 \delta_{NT}(\hat{\boldsymbol{F}}_u - \boldsymbol{H}\boldsymbol{F}_u) \\
&= \delta_{NT}^{-2} O_p(1) + \delta_{NT}^{-1} O_p(1).
\end{aligned}$$

Therefore the right-hand side of (A3) is $O_p(T^{-1/2}) + O_p(1)O_p(\delta_{NT}^{-1}) = O_p(\delta_{NT}^{-1})$. This implies that $\hat{\boldsymbol{\alpha}}' - \boldsymbol{\alpha}'\boldsymbol{H}^{-1}$ is $O_p(\delta_{NT}^{-1})$. Putting this back into (A2), we see therefore that $\hat{\boldsymbol{\alpha}}'\hat{\boldsymbol{F}}_t - \boldsymbol{\alpha}'\boldsymbol{F}_t$ is $O_p(1)O_p(\delta_{NT}^{-1}) + O_p(\delta_{NT}^{-1})O_p(1) = O_p(\delta_{NT}^{-1})$ which completes the result. □

A.3 Proof of Theorem 2

Proof. For each i, the first stage quantile regression coefficient is given by

$$(\hat{\gamma}_{0i}, \hat{\gamma}_i) = arg \min_{\gamma_0, \gamma} \frac{1}{T}\sum \rho_\tau(y_{t+h} - \gamma_0 - \gamma x_{it}). \tag{A4}$$

Consider the infeasible quantile regression of y_{t+h} on $(x_{it}, \boldsymbol{g}'_t, \varepsilon_{it})'$, yielding coefficient estimates

$$(\dot{\gamma}_{0i}, \dot{\gamma}_i, \dot{\boldsymbol{\gamma}}'_{ig}, \dot{\gamma}_{i\varepsilon})' = arg \min_{\gamma_0, \gamma, \boldsymbol{\gamma}_g, \gamma_\varepsilon} \frac{1}{T}\sum_{t=1}^{T} \rho_\tau(y_{t+h} - \gamma_0 - \gamma x_{it} - \boldsymbol{\gamma}'_g \boldsymbol{g}_t - \gamma_\varepsilon \varepsilon_{it}).$$

Note that f_t linearly depends on the vector $(x_{it}, \boldsymbol{g}'_t, \varepsilon_{it})'$. By White (1994) Corollary 5.12 and the equivariance properties of quantile regression, These coefficients satisfy

$$\sqrt{T}(\dot{\gamma}_i, \dot{\boldsymbol{\gamma}}'_{ig}, \dot{\gamma}_{i\varepsilon})' \xrightarrow[T\to\infty]{d} N\left(\left(\frac{\alpha}{\phi_i}, -\frac{\alpha}{\phi_i}\boldsymbol{\psi}'_i, -\frac{\alpha}{\phi_i}\right)', \boldsymbol{\Sigma}_\gamma\right)$$

ACF (2006) Theorem 1 implies that

$$\hat{\gamma}_i = \dot{\gamma}_i + \left(\sum_{u=1}^{T} w_{iu} x_{iu}^2\right)^{-1} \left(\sum_{u=1}^{T} w_{iu} x_{iu}\left(\dot{\boldsymbol{\gamma}}'_{ig}\boldsymbol{g}_u + \dot{\gamma}_{i\varepsilon}\varepsilon_{iu}\right)\right). \tag{A5}$$

for the weight $w_{it} = \frac{1}{2}\int_0^1 (1-u)\pi_\tau\left(u\left[x_{it}\hat{\gamma}_i - \mathbb{Q}\left(y_{t+h}|f_t\right)\right]|f_t\right)du$.[34] Expanding the weight around $x_{it} = 0$, we have

$$w_{it} = \sum_{n=1}^{\infty} \kappa_n(f_t) x_{it}^n \quad , \quad \kappa_n(f_t) \equiv \frac{1}{n!}\left.\frac{\partial^n w_{it}}{(\partial x_{it})^n}\right|_{x_{it}=0} \tag{A6}$$

and can use this to rewrite (A5). Note that $\kappa_n(f_t)$ is a function *only* of f_t and is therefore independent of $\boldsymbol{g}_t, \varepsilon_{it}$. Also note that $x_{it}^n = \sum_{j=0}^{n}(\phi_i f_t)^{n-j}(\boldsymbol{\psi}'\boldsymbol{g}_t + \varepsilon_{it})^j a_{n,j}$, where the $a_{n,j}$'s are polynomial expansion coefficients. Using the following notation

$$\Gamma_1 = \left(\sum_{u=1}^{T} w_{iu} x_{iu}^2\right)^{-1} \left(\sum_{u=1}^{T} w_{iu} x_{iu}\left[(\dot{\boldsymbol{\gamma}}_{ig} + \frac{\alpha}{\phi_i}\boldsymbol{\psi}_i)'\boldsymbol{g}_u + (\dot{\gamma}_{i\varepsilon} + \frac{\alpha}{\phi_i})\varepsilon_{iu}\right]\right),$$

$$\Gamma_2 = -\frac{\alpha}{\phi_i}\left(\frac{1}{T}\sum_{u=1}^{T} w_{iu} x_{iu}^2\right)^{-1} \left(\sum_{n=0}^{\infty}\sum_{j=0}^{n+1} a_{n+1,j}\left[\frac{1}{T}\sum_{u=1}^{T}\kappa_n(f_u)(\phi_i f_u)^{n+1-j}(\boldsymbol{\psi}'_i\boldsymbol{g}_u + \varepsilon_{iu})^{j+1}\right.\right.$$
$$\left.\left. - \mathbb{E}\left(\kappa_n(f_u)(\phi_i f_u)^{n+1-j}(\boldsymbol{\psi}'_i\boldsymbol{g}_u + \varepsilon_{iu})^{j+1}\right)\right]\right),$$

$$\Gamma_3 = -\frac{\alpha}{\phi_i} \times \left(\sum_{n=0}^{\infty}\sum_{j=0}^{n+1} a_{n+1,j}\mathbb{E}\left(\kappa_n(f_u)(\phi_i f_u)^{n+1-j}(\boldsymbol{\psi}'_i\boldsymbol{g}_u + \varepsilon_{iu})^{j+1}\right)\right)$$
$$\left(\sum_{n=0}^{\infty}\sum_{j=0}^{n+2} a_{n+2,j}\left[\mathbb{E}\left(\kappa_n(f_u)(\phi_i f_u)^{n+2-j}(\boldsymbol{\psi}'_i\boldsymbol{g}_u + \varepsilon_{iu})^{j}\right) - \frac{1}{T}\sum_{u=1}^{T}\kappa_n(f_u)(\phi_i f_u)^{n+2-j}(\boldsymbol{\psi}'_i\boldsymbol{g}_u + \varepsilon_{iu})^{j}\right]\right)^{-1},$$

$$\Gamma_4 = \dot{\gamma}_i - \frac{\alpha}{\phi_i},$$

[34] This weight comes from the fact that in our factor model the true conditional quantile $\mathbb{Q}(y_{t+h}|\mathcal{I}_t)$ is identical to the quantile conditioned only on f_t. In addition, the conditioning of π_τ on f_t is a choice of representation and consistent with our assumption that no other time t information influences the distribution of η_{t+h}. ACF provide a detailed derivation of this weight as a function of the quantile forecast error density, which they denote as f rather than π.

we can rewrite (A5) as

$$\hat{\gamma}_i = \frac{\alpha}{\phi_i} - \frac{\alpha}{\phi_i}\frac{\sum_{n=0}^{\infty}\sum_{j=0}^{n+1} a_{n+1,j}\mathbb{E}\left[K_n(f_t)(\phi_i f_t)^{n+1-j}\right]\sum_{k=0}^{j+1} a_{j+1,k}\mathbb{E}\left[(\boldsymbol{\psi}_i'\boldsymbol{g}_t)^{j+1-k}\right]\mathbb{E}\left[\varepsilon_{it}^k\right]}{\sum_{n=0}^{\infty}\sum_{j=0}^{n+2} a_{n+2,j}\mathbb{E}\left[K_n(f_t)(\phi_i f_t)^{n+2-j}\right]\sum_{k=0}^{j} a_{j,k}\mathbb{E}\left[(\boldsymbol{\psi}_i'\boldsymbol{g}_t)^{j-k}\right]\mathbb{E}\left[\varepsilon_{it}^k\right]} + \Gamma_1 + \Gamma_2 + \Gamma_3 + \Gamma_4. \tag{A7}$$

Because of the probability limit noted above for $(\dot{\gamma}_i, \dot{\boldsymbol{\gamma}}_{ig}', \dot{\gamma}_{i\varepsilon})'$, we know that Γ_1 and Γ_4 are $O_p(T^{-1/2})$. Γ_2 and Γ_3 are also $O_p(T^{-1/2})$ by Assumption 4, the continuous mapping theorem, and the law of large numbers. By Assumption 4, for any i and for n odd we have $\mathbb{E}\left[(\boldsymbol{\psi}_i'\boldsymbol{g}_t)^n\right] = 0$. Therefore we can rewrite the above expression for $\hat{\gamma}_i$ as

$$\hat{\gamma}_i = \frac{\alpha}{\phi_i} - \frac{\alpha}{\phi_i}\Upsilon(\boldsymbol{\psi}_i^2, \phi_i) + O_p(T^{-1/2})$$

where Υ is a rational function given by the second term in A7.

The second stage factor estimate is[35]

$$\begin{aligned}\hat{f}_t &= \frac{1}{N}\sum_{i=1}^{N}\left(\hat{\gamma}_i - \bar{\hat{\gamma}}\right)(x_{it} - \bar{x}_t) \\ &= \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\alpha}{\phi_i} - \frac{\alpha}{\phi_i}\Upsilon(\boldsymbol{\psi}_i^2, \phi_i) + O_p(T^{-1/2}) - \bar{\hat{\gamma}}\right)\left((\phi_i - \bar{\phi})f_t + (\boldsymbol{\psi}_i - \bar{\boldsymbol{\psi}})'\boldsymbol{g}_t + (\varepsilon_{it} - \bar{\varepsilon}_t)\right).\end{aligned}$$

Because the irrelevant factor $\boldsymbol{g}_t$ is multiplied by $N^{-1}\sum_i(\frac{\alpha}{\phi_i} - \frac{\bar{\alpha}}{\phi_i})(\boldsymbol{\psi}_i - \bar{\boldsymbol{\psi}})'$, $\boldsymbol{g}_t$ vanishes from $\hat{f}_t$ for N large due to the independence of $\phi_i, \boldsymbol{\psi}_i$. Sums involving cross products of $\Upsilon(\boldsymbol{\psi}_i^2, \phi_i)$ and $(\boldsymbol{\psi}_i - \bar{\boldsymbol{\psi}})'$ vanish in probability as N becomes large by the symmetry of $\boldsymbol{\psi}_i$ (Assumption 4) and Lemma 1. Sums involving ε_{it} vanish as N becomes large by the independence of ε_{it} and $(\phi_i, \boldsymbol{\psi}_i')'$. Straightforward algebra shows that $\hat{f}_t - hf_t$ is at least $O_p(\delta_{NT}^{-1})$, where is h a finite nonzero constant.[36] From here, Theorem 1's argument, starting in the second paragraph of that proof, goes through for $\hat{\alpha}\hat{f}_t$ and the result follows. □

Lemma 1. *For any symmetrically-distributed random variable x, random vector $\boldsymbol{y} = (y_1, ..., y_{d-1})$ such that $x \perp \boldsymbol{y}$, and rational function $f : \mathcal{R}^d \to \mathcal{R}^1$ that is infinitely differentiable at some number $\boldsymbol{a} \in \mathcal{R}^d$, it is the case that $Cov(f(x^2, \boldsymbol{y}), x) = 0$.*

Proof. Define the vector $\boldsymbol{x} = (x^2, \boldsymbol{y}')'$, so that $x_1 = x^2$ and $x_j = y_{j-1}$. The Taylor

[35] Overbar denotes a sample mean over i.

[36] It can be shown that

$$N^{-1}\sum_{i=1}^{N}\left(\Upsilon(\boldsymbol{\psi}_i^2, \phi_i) - N^{-1}\sum_{j=1}^{N}\Upsilon(\boldsymbol{\psi}_j^2, \phi_j)\right)(\phi_i - \bar{\phi})$$

converges to a finite constant that is different from one, which implies that h is nonzero.

series for $f(\boldsymbol{x})$ at $\boldsymbol{a}$ is

$$f(a_1, \ldots, a_d) + \sum_{j=1}^{d} \frac{\partial f(a_1, \ldots, a_d)}{\partial x_j}(x_j - a_j) + \frac{1}{2!}\sum_{j=1}^{d}\sum_{k=1}^{d} \frac{\partial^2 f(a_1, \ldots, a_d)}{\partial x_j \partial x_k}(x_j - a_j)(x_k - a_k) + \\ + \frac{1}{3!}\sum_{j=1}^{d}\sum_{k=1}^{d}\sum_{l=1}^{d} \frac{\partial^3 f(a_1, \ldots, a_d)}{\partial x_j \partial x_k \partial x_l}(x_j - a_j)(x_k - a_k)(x_l - a_l) + \ldots$$

Any cross products involving x_j for $j > 1$ have zero covariance with x by independence. By the symmetry of x, $Cov(x_1^i, x) = 0$ for any $i = 0, 1, ...$, which proves the result. □

A.4 Simulation Evidence

Table A1 compares PCQR and PQR estimates with the true 0.1 conditional quantile. We report the time series correlation between the true conditional quantile and the fitted series as well as the time series mean absolute error (MAE) averaged over simulations. The simulated model is

$$\begin{aligned} y_{t+1} &= -f_t \mathbb{1}_L + (\sigma_\eta + f_t \mathbb{1}_S)\,\eta_{t+1} \\ \boldsymbol{x}_t &= \boldsymbol{\phi} f_t + \boldsymbol{\psi} g_t + \boldsymbol{e}_t \end{aligned}$$

We draw $f \sim U(0,1)$, $g \sim N(0, 0.5^2)$, $e_{it} \sim N(0, 0.5^2)$, $\eta \sim N(0, 0.5^2)$, $\phi_i \sim N(0, 0.5^2)$, and $\psi_i \sim N(0, 0.5^2)$, all independent. We pick $\mathbb{1}_L = 1$ for a location model and $\mathbb{1}_L = 0$ otherwise, $\mathbb{1}_S = 1$ for a scale model and $\mathbb{1}_S = 0$ otherwise, and $\mathbb{1}_L = \mathbb{1}_S = 1$ for a location and scale model. We vary T, set $N = T$, and run 1,000 simulations of each specification. The table reports performance of quantile forecasts from PCQR using two principal component indexes and from PQR using a single index. It shows that conditional quantile forecasts are increasingly accurate in the size of the predictor panel. As N and T grow, the time series correlation between fits and the true conditional quantile approaches one and the forecast error shrinks toward zero.

B Empirical Appendix

B.1 Systemic Risk Measures

CoVaR and ΔCoVaR (Adrian and Brunnermeier 2011) CoVaR is defined as the value-at-risk (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 (computed at quantile q):

$$Pr(X^i < \text{VaR}^i) = q$$

CoVaR for institution i is then defined as:

$$Pr(X^{syst} < \text{CoVaR}^i | X^i = \text{VaR}^i) = q$$

which we estimate using conditional linear quantile regression after estimating VaR^i. ΔCoVaR^i is defined as the VaR of the financial system when institution i is at quantile q (in distress) relative to the VaR when institution i is at the median of its distribution:

$$\Delta\text{CoVaR}^i = \text{CoVaR}^i(q) - \text{CoVaR}^i(0.5).$$

In estimating CoVaR, we set q to the 5th percentile. Note that Adrian and Brunnermeier (2011) propose the use of a conditional version of CoVaR as well, called *forward* CoVaR, in which the relation between the value-at-risk of the system and an individual institution is allowed to depend on an additional set of covariates. Here we use the alternative approach of rolling window CoVaR estimates with an estimation window of 252 days. We construct individual CoVaR for each firm separately and calculate the aggregate measure as an equal-weighted average among the largest 20 financial firms.

MES (Acharya, Pedersen, Philippon and Richardson (2010)) These measures capture the exposure of each individual firm to shocks to the aggregate system. MES captures the expected return of a firm conditional on the system being in its lower tail:

$$\text{MES}^i = E[R^i | R^m < q]$$

where q is a low quantile of the distribution of R_m (we employ the 5th percentile). We construct individual MES for each firm separately using a rolling window of 252 days and calculate the aggregate measure as an equal-weighted average among the largest 20 financial firms.

MES-BE (Brownlees and Engle (2011)) This version of MES employs dynamic volatility models (GARCH/DCC for $\sigma_{\cdot,t}, \rho_t$) to estimate the components of MES:

$$\text{MES-BE}_{i,t-1} = \sigma_{i,t}\rho_t E\left[\epsilon_{m,t} | \epsilon_{m,t} < \frac{k}{\sigma_{m,t}}\right] + \sigma_{i,t}\sqrt{1-\rho_t^2} E\left[\epsilon_{i,t} | \epsilon_{m,t} < \frac{k}{\sigma_{m,t}}\right].$$

where $\epsilon_{m,t}$ are market return shocks, $\epsilon_{i,t}$ is the individual firm return and k is set to 2 following Brownlees and Engle (2011). We construct the measure individually for each firm and calculate the aggregate measure as an equal-weighted average among the largest 20 financial firms.

Absorption Ratio (Kritzman et al. (2010)) This measure computes the fraction of return variance of a set of N financial institutions explained by the first $K < N$ principal components:

$$\text{Absorption}(K) = \frac{\sum_{i=1}^{K} Var(PC_i)}{\sum_{i=1}^{N} Var(PC_i)}.$$

A leading distress indicator is then constructed as the difference between absorption ratios calculated for long and short estimation windows

$$\Delta\text{Absorption}(K) = \text{Absorption}(K)_{\text{short}} - \text{Absorption}(K)_{\text{long}}.$$

In our empirical analysis we construct the Absorption(3) measure using returns for the largest 20 financial institutions at each point in time. We construct ΔAbsorption(3) using 252 and 22 days for the long and short windows, respectively.

Dynamic Causality Index or DCI (Billio et al. 2012) The index aims to capture how interconnected a set of financial institutions is by computing the fraction of significant Granger-causality relationships among their returns:

$$\text{DCI}_t = \frac{\#\, significant\, GC\, relations}{\#\, relations}$$

A Granger-causality relation is defined as significant if its p-value falls below 0.05. We construct the measure using daily returns of the largest 20 financial institutions, with a rolling window of 36 months.

International Spillover (Diebold and Yilmaz 2009) The index, downloaded from http://economicresearchforum.org/en/bcspill, aggregates the contribution of each variable to the forecast error variance of other variables across multiple return series. It captures the total extent of spillover across the series considered (a measure of interdependence).

Volatility We construct individual volatility series of financial institutions by computing the within-month standard deviation of daily returns. We construct the aggregated series of volatility by averaging the individual volatility across the 20 largest institutions.

Book and Market Leverage We construct a measure of aggregate book leverage (debt/assets) and aggregate market leverage (debt/market equity) among the largest 20 financial institutions to capture the potential for instability and shock propagation that occurs when large intermediaries are highly levered.

Size Concentration We construct the Herfindal index of the size distribution among financial firms:

$$\text{Herfindahl}_t = N \frac{\Sigma_{i=1}^{N} ME_i^2}{(\Sigma_{i=1}^{N} ME_i)^2}$$

The concentration index captures potential instability due to the threat of default of the largest firms. The index corrects for the changing number of firms in the sample by multiplying the measure of dispersion by the number of firms, N. When constructing this measure we use the market equity of the largest 100 firms.

Turbulence (Kritzman and Li (2010)) Turbulence is a measure of excess volatility that compares the realized squared returns of financial institutions with their historical volatility:

$$\text{Turbulence}_t = (r_t - \mu)' \Sigma^{-1} (r_t - \mu)$$

where r_t is the vector of returns of financial institutions, and μ and Σ are the historical mean and variance-covariance matrix. We compute the moments using data for the largest 20 financial institutions and a rolling window of 60 months.

AIM (Amihud 2002) AIM captures a weighted average of stock-level illiquidity AIM_t^i, defined as:

$$\text{AIM}_t^i = \frac{1}{K} \sum_{\tau=t-K}^{t} \frac{|r_{i,\tau}|}{turnover_{i,\tau}}$$

We construct an aggregated measure by averaging the measure across the top 20 financial institutions.[37]

TED Spread The difference between three-month LIBOR and three-month T-bill interest rates.

Default Yield Spread The difference between yields on BAA and AAA corporate bonds. The series is computed by Moody's and is available from the Federal Reserve Bank of St. Louis.

Term Spread The difference between yields on the ten year and the three month US Treasury bond. The series is obtained from Global Financial Data.

[37] Our definition of AIM differs from that of Amihud (2002). We replace dollar volume with share turnover to avoid complications due to non-stationarity.

B.2 Macroeconomic Shocks

Let the monthly macroeconomic series (CFNAI or IP) be denoted Y_t. We construct shocks to these series as residuals in an autoregression of the form

$$Y_t = c + \sum_{l=1}^{p} a_l Y_{t-l} = c_p + a_p(L)Y_t$$

for a range of autoregressive orders, p, and select the p that minimizes the Akaike Information Criterion. This approach purges each macroeconomic variable of predictable variation based on its own lags, and is a convention in the macro forecasting literature (e.g. Bai and Ng (2008b) and Stock and Watson (2012)).

Shocks are estimated in a recursive out-of-sample scheme to avoid look-ahead bias in our out-of-sample quantile forecasting tests. For each month τ, we estimate the AR and AIC on data only known through τ, and construct the forecast residual at time $\tau + 1$ based on these estimates. Finally, we construct quarterly shocks as a moving three-month sum of the monthly residuals.

B.3 Quantile Granger Causality Tests

An alternative to the pre-whitening procedure described in Appendix B.2 is to control for the history each dependent variable within the quantile regression specification, as in an in-sample Granger causality test. This alternative procedure yields qualitatively similar results to those reported in the main text.

To conduct a Granger causality test in our framework, consider the quantile regression

$$\mathbb{Q}_\tau(Y_t|\mathcal{I}_t) = \beta_0 + \sum_{l=1}^{p} \beta_p Y_{t-p} + \sum_{k=1}^{q} \gamma_k x_{t-k}$$

where Y is monthly IP growth and x is a systemic risk measure. We investigate whether x Granger causes the quantiles of Y by testing the hypothesis: $\gamma_1 = \cdots = \gamma_q = 0$. We estimate the standard error matrix of $(\boldsymbol{\beta}', \boldsymbol{\gamma}')'$ using Politis and Romano's (1994) stationary block-bootstrap with 1,000 bootstrap replications and choose $q = 1$. Table A2 reports the resulting Wald statistics for the 20^{th} percentile, median and 80^{th} percentile, each of which is asymptotically distributed as a $\chi^2(1)$.

B.4 Tests of Coefficient Equality

In Section 5.1 we test the hypothesis that the median quantile regression coefficient equals the 20^{th} percentile regression coefficient. The test statistics are formed via a bootstrap algorithm for each predictor separately. These are calculated by resampling the estimated residuals to create 1,000 bootstrapped data series, calculating the difference between the estimated 20^{th} and 50^{th} percentile regression coefficients for each bootstrap sample, and reporting the t-statistic as the mean of this difference divided by the standard deviation of this difference across bootstrap samples.

B.5 VAR

We use Bloom's (2009) data from June 1962 to June 2008. The vector process is defined as $\boldsymbol{Y}_t = (sp500_t, aggvol_t, finvol_t, wage_t, price_t, ff_t, hours_t, empl_t, ip_t)$, where $sp500$ is the log of the S&P500 stock market index, *aggvol* is aggregate equity market volatility, *finvol* is financial sector equity volatility, *ff* is the Federal Funds rate, *wage* is the log of average hourly earnings, *price* is the log of the consumer price index, *hours* is average hours worked, *empl* is the log of employment, and *ip* is the log of industrial production. Equity volatility is measured as the volatility of daily returns within each month for the portfolio of all firms (*aggvol*) or all financial firms (*finvol*) in CRSP. Following Bloom (2009), all variables are Hodrick-Prescott detrended with a smoothing parameter of 129,600, including the volatility variables. This differs slightly from Bloom's (2009) specification, in which *aggvol* takes a value of 1 in the 17 months when stock market volatility spikes 1.65 standard deviations above mean and zero otherwise. We use a continuous specification to directly compare impulse response functions for shocks to aggregate and financial volatility.

The VAR then takes the form

$$\boldsymbol{Y}_t = \sum_{j=1}^{12} \boldsymbol{A}_j \boldsymbol{Y}_{t-j} + \boldsymbol{u}_t.$$

Our use of twelve monthly lags follows Bloom (2009). We assume $\boldsymbol{u}_t$ is serially uncorrelated. The recursive identification scheme (see Sims 1980) assumes that

$$\boldsymbol{u}_t = \boldsymbol{C}\boldsymbol{\epsilon}_t$$

where $\mathbb{E}(\boldsymbol{\epsilon}_t) = \boldsymbol{0}$, $\mathbb{E}(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t') = \boldsymbol{I}$, and $\boldsymbol{C}$ is a lower triangular matrix. The structural shocks are found from a Cholesky factorization of the sample covariance matrix of the estimated residuals $\hat{\boldsymbol{u}}_t$, and then the impulse responses follow from the estimated dynamics $\{\hat{\boldsymbol{A}}_1, \ldots, \hat{\boldsymbol{A}}_{12}\}$. We present bootstrapped confidence intervals with 68% coverage, which are the finite-sample analogues of the one-standard-deviation asymptotic standard-error bands studied by Bloom (2009). We follow Efron and Tibshirani (1993) in bootstrapping confidence bands for the impulse response functions. These are calculated by resampling the estimated residuals to create 1,000 bootstrapped data series, estimating the impulse response functions on each bootstrap sample, and reporting the 68% coverage intervals of these estimates in each period.

Table A1: Simulation Evidence

	Location		Scale		Loc. and Scale	
T, N	Corr.	MAE	Corr.	MAE	Corr.	MAE
			Panel A: PCQR			
$T, N = 50$	0.87	0.61	0.76	2.77	0.89	0.50
$T, N = 100$	0.94	0.33	0.85	6.39	0.95	0.28
$T, N = 500$	0.99	0.12	0.98	0.16	0.99	0.11
$T, N = 1,000$	0.99	0.08	0.99	0.11	1.00	0.07
			Panel B: PQR			
$T, N = 50$	0.74	0.80	0.56	3.07	0.72	0.90
$T, N = 100$	0.84	0.51	0.70	1.06	0.84	0.54
$T, N = 500$	0.96	0.22	0.91	0.33	0.96	0.21
$T, N = 1,000$	0.98	0.15	0.95	0.22	0.98	0.15

Notes: Simulation evidence using the model described in the text. We consider dimensions for T, N between 50 and 1,000. We report time series correlation and mean absolute pricing error between the true and estimated 0.1 conditional quantiles. Panel A reports results for PCQR using two principal component indexes, and Panel B reports results for PQR using a single index. The simulated model is described in Appendix A.

Table A2: Quantile Forecasts of US IP Growth Using Granger Causality Tests

	20^{th}	Median	80^{th}
Absorption	0.04	2.74*	9.86***
AIM	73.32***	0.00	27.33***
CoVaR	10.86***	12.99***	11.38***
ΔCoVaR	8.70***	4.81**	7.04***
MES	6.29**	4.41**	5.21**
MES-BE	0.03	0.00	0.42
Book Lvg.	0.35	1.35	0.17
DCI	0.13	0.13	1.07
Def. Spr.	7.53***	19.16***	11.84***
ΔAbsorption	0.03	0.08	0.50
Intl. Spillover	0.21	1.70	1.37
Size Conc.	0.01	0.00	0.01
Mkt. Lvg.	12.47***	7.29***	0.00
Volatility	12.62***	21.15***	5.34**
TED Spr.	3.80*	0.03	0.43
Term Spr.	0.90	1.09	0.91
Turbulence	13.56***	7.17***	0.04

Notes: The table reports Wald statistics of the test that the systemic risk measure (by row) does not Granger cause (in the quantile sense) IP growth in the regression at a particular quantile (by column). Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample period is 1946-2011. Rows "Absorption" through "Turbulence" use each systemic risk measure (by row) singly in a quantile regression. "Multiple QR" uses the systemic risk measures "Absorption" through "Turbulence" jointly in a quantile regression.

Table A3: 20^{th} Percentile US IP Growth Forecasts, Excluding the Recent Crisis

	In-Sample	Out-of-Sample		
Out-of-sample start:		1950	1970	1990
Panel A: Individual Systemic Risk Measures				
Absorption	0.03	−2.82	−4.71	−4.65
AIM	4.68***	3.96***	6.17**	9.92***
CoVaR	2.03**	0.54	−0.19	−4.52
ΔCoVaR	0.42	−1.25	−2.55	−5.61
MES	0.45	−1.21	−1.99	−4.58
MES-BE	2.47**	1.78***	5.45***	7.19***
Book Lvg.	1.47**	–	–	5.00***
DCI	0.03	−1.23	−1.01	−1.51
Def. Spr.	0.55	−2.11	−2.85	2.97***
ΔAbsorption	0.17	−0.88	−0.09	−0.30
Intl. Spillover	0.02	–	1.99	6.34***
Size Conc.	0.02	−2.72	−8.77	−5.47
Mkt. Lvg.	7.68***	–	–	9.10**
Volatility	1.45*	0.64	1.38	−4.06
TED Spr.	0.89***	–	–	9.61**
Term Spr.	2.23**	0.87	3.58**	4.57*
Turbulence	1.40*	0.88	2.24**	3.04
Panel B: Systemic Risk Indexes				
Multiple QR	19.32***	−28.51	−27.56	5.29
PCQR1	−0.71	−0.80	−2.96	−6.01
PCQR2	11.90***	4.93**	8.12***	13.25***
PQR	11.93***	6.28***	10.89***	13.26***

Notes: The table reports quantile forecast R^2 (in percentage) relative to the historical quantile model. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample is 1946-2007. In-sample statistics are in column one. The out-of-sample start is noted for columns two through four. Rows "Absorption" through "Turbulence" use each systemic risk measure in a univariate quantile forecast regression for IP growth rate shocks in the US. "Multiple QR" uses all systemic risk measures jointly in a multiple quantile regression. Rows "PCQR1" through "PQR" use dimension reduction techniques on all the systemic risk measures. PCQR1 and PCQR2 use one and two principal components, respectively, in the PCQR forecasting procedure, while PQR uses a single factor. Owing to its late availability, TED Spr. is excluded from Multiple QR and PCQR calculations. "–" indicates insufficient data for estimation in a given sample.