Systemic risk and the macroeconomy: An empirical evaluation

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ABSTRACT

This article studies how systemic risk and financial market distress affect the distribution of shocks to real economic activity. We analyze how changes in 19 different measures of systemic risk skew the distribution of subsequent shocks to industrial production and other macroeconomic variables in the US and Europe over several decades. We also propose dimension reduction estimators for constructing systemic risk indexes from the cross section of measures and demonstrate their success in predicting future macroeconomic shocks out of sample.

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1. Introduction

The financial crisis of 2007–2009 has made systemic risk a focal point of research and policy, and has established the financial sector as its center of analysis. The empirical side of the literature focuses on measuring distress in financial markets. This has produced a staggering variety of systemic risk proxies, many hoping to serve as an early warning signal of market dislocations like those observed during the crisis.

In this paper, we investigate how a buildup of systemic risk in the financial sector increases risks in the real economy. Specifically, we exploit the large set of existing measures of financial sector distress to quantify how fluctuations in systemic risk impact the probability of a macroeconomic downturn. We propose a new systemic risk index that efficiently aggregates recession-relevant information across the gamut of individual measures. We show that increases in the index are associated with a large widening
of the left tail of economic activity. A one standard deviation increase in systemic risk shifts the 20th percentile of the industrial production (IP) growth shock distribution downward by more than 50%, from around −1.4% unconditionally, to −2.2% (annualized). In several occasions in US history (including during the recent financial crisis), the conditional 20th percentile was below −3%, twice as large as in normal times. In addition, we show that the systemic risk index also predicts reactions of policymakers: the 20th percentile of innovations in the Federal Funds rate drops by 60%, from −50 basis points (bps) to −80 bps.

Our analysis uses out-of-sample predictive quantile regression, which forecasts how specific features of the macroeconomic shock distribution respond to systemic risk. We argue that a quantile approach is appropriate for evaluating the potentially asymmetric and nonlinear association between systemic risk and the macroeconomy that has been emphasized in the theoretical literature. These theories predict that distress in the financial system can amplify adverse fundamental shocks and result in severe downturns or crises, while the absence of stress does not necessarily trigger a macroeconomic boom. Quantile regression is a flexible tool for investigating the impact of systemic risk on the left tail of macroeconomic shocks, as opposed to focusing on their central tendency via least squares.

We examine 19 previously proposed measures of systemic risk in the US and ten 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 long time series and international panel provide empirical insights over several business cycles, in contrast to much of the literature’s emphasis on the 2007–2009 sample in the US.

We first investigate each systemic risk measure individually, asking whether or not it provides significant out-of-sample information about future macroeconomic shocks. Next, we ask whether it is possible to aggregate risk measures into a systemic risk index to enhance forecasting power. A naive way to do this is by including all the measures as separate right-hand-side variables in a multiple quantile regression. But we find that this approach has virtually no out-of-sample forecasting power. This is due to multiple quantile regression overfitting the sample data, analogous to well-understood problems of overfit in multiple least squares regression (e.g., Stock and Watson, 2006).

As an alternative, we propose dimension reduction techniques for a conditional quantile factor model. We show how these estimators may be used to construct systemic risk indexes with theoretically attractive asymptotic properties. Most importantly, we demonstrate their significant forecasting power in our empirical setting. We derive these estimators as a solution to 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?

The first solution 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. The second solution is partial quantile regression (PQR), which is an adaptation of partial least squares to the quantile setting. We prove that both approaches consistently estimate conditional quantiles of macroeconomic shocks under mild conditions. We also show that PQR, our preferred estimator, produces consistent quantile forecasts with typically fewer factors than PCQR.

A set of new stylized facts emerges from our empirical investigation. First, we find that a select few systemic risk measures possess significant predictive content for the downside quantiles of macroeconomic shocks such as innovations in IP growth or the Chicago Fed National Activity Index. Measures of financial sector equity volatility perform well in a variety of specifications; other variables, including leverage and liquidity measures, work well in some specifications but not others.

Next, we find that dimension-reduced systemic risk indexes reveal robust dependence between systemic risk and the probability of future negative macroeconomic shocks. In particular, our novel PQR estimator achieves significant forecast improvements across macroeconomic variables in a wide range of specifications.

Third, systemic risk measures are more informative about the left tail of macroeconomic shocks than about their central tendency or right tail. This is evident not only for systemic risk indexes, but is uniformly true across individual measures as well. This supports the idea that systemic risk is an inherently asymmetric and nonlinear phenomenon, a feature emphasized in much of the theoretical literature.

Next, we show that measures of financial sector equity volatility are the most useful individual predictors of macroeconomic downturns. In contrast, equity volatility in the nonfinancial sector appears to have little, if any, predictive power. This suggests that economic mechanisms connecting aggregate stock market volatility to the real economy, such as the uncertainty shocks mechanism in Bloom (2009), may blur an important distinction between

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3 See, for example, Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Bernanke, Gertler, and Gilchrist (1999), Brunnermeier and Sorkin (2014), 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 used 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 covariance with the forecast target, choosing a linear combination of predictors that is a consistent quantile forecast. 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.
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