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# Measuring systemic risk with regime switching in tails

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## ABSTRACT

This paper motivates the importance of modeling nonlinearities in measuring systemic risk. I capitalize this motivation by generalizing the *CoVaR* approach proposed by Adrian and Brunnermeier (2016) to allow it switching between a high and a normal risk regime filtered from data.. Considering the U.S. large bank holding companies (BHCs), this paper shows that modeling regime changes in tails is capable of capturing both amplification and mean-reversion effects of an adverse shock to a bank's balance sheet on the banking system. Using the Kolmogorov–Smirnov test statistics with and without bootstrapping, I perform the significance test to identify systemically important financial institutions (SIFIs), and the stochastic dominance test to rank the identified SIFIs. The stochastic dominance test raises the concern that the *CoVaR* measure underestimates systemic risk contributions for SIFIs but overestimates for non-SIFIs. Finally, applying the BHCs' characteristics and housing market price to forecast the regime-switching systemic risk out-of-sample, I obtain from 4- and 8-quarter-ahead horizons a desirable *countercyclical, forward-looking* measure of systemic risk.

#### 1. Introduction

The Financial Stability Oversight Council (FSOC) has three broad mandates: (i) to identify and monitor excessive risks to the U.S. financial system arising from the distress or failure of large, interconnected financial institutions; (ii) to eliminate expectations that any American financial firm is "too big to fail"; (iii) to respond to emerging threats to the stability of the financial system.<sup>1</sup> The essential point for all these directives is the accurate and timely measurement of systemic risk. Nonetheless, due to the complex and adaptive nature of the financial system, a diversity of models and measures have been developed in the literature that emphasize different aspects of systemic risk, e.g., credit default swaps (Huang et al., 2009), multivariate extreme value theory (Zhou, 2010), systemic expected shortfall (Acharya, 2010), principal components and Granger-causality networks (Billio et al., 2012), marginal expected shortfall (Brownlees and Engle, 2015), etc. See Bisias et al. (2012) for a comprehensive survey in systemic risk analytics.

Recently, Adrian and Brunnermeier (2016) (AB henceforth) propose the  $\Delta CoVaR$  approach to measure systemic risk contributions defined as the difference between the value-at-risk (VaR) of the financial system conditional on an institution being in distress and the VaR of the financial system conditional on the same institution

being in its normal state. Regressing quantiles, they directly estimate tail comovements between the financial system and a financial institution to characterize the propagation of adverse shocks to a single institution through the rest of the system. In a comparison study, Sedunov (2016) finds that the  $\Delta CoVaR$  measure outperforms systemic expected shortfall (Acharya, 2010) and Granger causality (Billio et al., 2012) in forecasting future systemic risk exposures.

This  $\Delta CoVaR$  measure of systemic risk contributions is particularly appealing in stress-testing financial institutions, as it outlines a method to construct a countercyclical, forward-looking systemic risk measure by predicting future systemic risk using macroeconomic variables and balance sheet deleveraging and – importantly – lagged observable characteristics of an institution, such as size, leverage, maturity mismatch, etc. In addition, the AB approach employs accounting data to calculate market-valued asset returns, in contrast to most of the alternative measures that omit balance sheet data. Furthermore, quantile regression does not require assuming a conditional distribution of returns and thus is robust to distribution misspecification. Due to the competitive merits, for the past few years, the AB approach has extensively been applied and extended both in the academic literature and by policymakers for a variety of financial systems.<sup>2</sup>

However, the linear quantile regression used to estimate  $\Delta CoVaR$  cannot accommodate many stylized facts such as structural breaks and

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<sup>&</sup>lt;sup>1</sup> The full range of detailed mandates, constraints, and authorities for the FSOC are covered in Sections 112–156 of the Act.

<sup>&</sup>lt;sup>2</sup> See e.g., International Monetary Fund (2009), Wong and Fong (2010), Van Oordt and Zhou (2010), Deutsche Bundesbank (2010), Roengiptya and Rungcharoenkitkul (2011), Fong et al. (2011), Brunnermeier et al. (2012), Lopez-Espinosa et al. (2012, 2015), Rodriguez-Moreno and Pena (2012), Girardi and Ergun (2013), Bernal et al. (2014), Castro and Ferrari (2014), etc. Critical assessments of market-based risk measures, including Δ*CoVaR*, can be found in Danielsson et al. (2011) and Loeffler and Raupach (2013).

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nonlinearities in macroeconomic and financial time series. To date, capturing nonlinear tail comovements between system-wide and individual bank returns has yet been considered in this fast-growing literature, except the recent work of Lopez-Espinosa et al. (2015) who estimate threshold quantile regressions for the  $\Delta CoVaR$  measure of systemic risk contributions. The authors find that ignoring the asymmetric feature of tail-interdependences leads to a severe underestimation of systemic risk.

In this respect, Bisias et al. (2012) and Brunnermeier and Oehmke (2013) also concern that the  $\Delta CoVaR$  approach is vulnerable to, e.g., nonstationarity and structural breaks based on historical data, which are particularly relevant to systemic risk measurement. Virtually the  $\Delta CoVaR$  measure of systemic risk contributions and inference rely on the assumption that the joint distribution of the relevant variables is stable over time. Nonetheless, the literature has recognized the stylized fact of structural breaks in macroeconomic and financial time series, so that the distribution structure of a time series might, driven by economic states, evolve over time. For instance, Qu (2008) argues that under various circumstances, structural change in conditional quantiles is of key importance. Therefore, without informing its associated economic states, the  $\Delta CoVaR$  measure is at best an averaged/mixed result over different economic regimes, and hence it is less advisable to or even misleads market participants and regulators.

This paper attempts to fill this literature gap by means of incorporating potential nonlinearities inherent in financial dynamics into systemic risk measure. To achieve this, I generalize the  $\Delta CoVaR$  approach by allowing the location and scale parameters subject to regime shifts in quantile regression, so that the joint distribution of targeted variables can evolve over time. Particularly, I rely on the Markov-switching quantile autoregression (MSQAR) of Liu (2016) to filter two specific risk regimes from data: a normal risk level implied by good economic periods and a high risk level associated with economic recessions, crises or extreme events. Note that the asymmetric responses of the financial system to an adverse shock to an institution, perhaps originating from different regimes, can also be captured if the parameters estimated from a normal and a high risk regime significantly differ.

Arguably from policy and regulatory perspectives, the generalized  $\Delta CoVaR$  measure with regime switching in tails ( $\Delta RSCoVaR$ ) fits better for the Supervisory Stress Scenario required by Federal Reserve Bank in Comprehensive Capital Analysis and Review (CCAR).<sup>3</sup> In CCAR, a supervisory stress scenario is a hypothetical scenario to be used to assess the strength and resilience of bank capital in a severely adverse economic environment in which the U.S. economy experiences a significant recession, i.e., significant declines in asset prices, a slowdown in global economic growth, etc. The AB approach is not suitable for this scenario because the single set of parameters estimated from a linear quantile regression reflects at most a response of the financial system to an institution averaged/mixed over different regimes if regime changes are present in data. However, the set of MSQAR parameters identified from the high risk regime associated with economic recessions and crises, if significantly different from that identified from the normal economic regime, should be applied more appropriately to stress-testing financial institutions under supervisory stress scenarios.

Moreover, the generalized measure of systemic risk contributions in this paper provides flexibility for testing a variety of hypothetically distressed scenarios. For instance, if an institution is systematically important, its hypothetically distressed scenario should also cause the financial system being in distress. The systemic risk of a systemically important institution can thus be measured by the high risk episodes of

<sup>3</sup> See Comprehensive Capital Analysis and Review 2012: Methodology and Results for Stress Scenario Projections. Board of Governors of the Federal Reserve System: March 13, 2012; and Comprehensive Capital Analysis and Review 2013: Assessment Framework and Results. Board of Governors of the Federal Reserve System: March 2013. the financial system conditional on the high risk episodes of the institution. By contrast, the hypothetically distress scenario of a nonsystemically important institution, unless leading to a herding effect, does not cause a distress in the financial system. Hence, its systemic risk might be obtained from the normal risk periods of the financial system conditional on the high risk episodes of the institution.

Considering large bank holding companies (BHCs) in the U.S., this paper empirically applies the proposed  $\Delta RSCoVaR$  methodology to estimate their systemic risk contributions to the banking system. More importantly, in order to identify systemically important banks and then rank the identified banks on the basis of the estimated systemic risk contributions, I conduct the significance and stochastic dominance tests of Bernal et al. (2014) and Castro and Ferrari (2014) to determining: (i) whether or not a bank can be classified as a SIFI; (ii) and whether or not, according to  $\Delta RSCoVaR$ , one bank is systemically riskier than another.

Several key findings in this paper are highlighted as follows. First, the empirical results show that the banking system might positively respond to an adverse shock to a bank's balance sheet (an amplification effect) during a high risk regime but negatively (a mean-reversion effect) during a normal risk regime or vice versa.<sup>4</sup> Therefore, the empirical evidence supports the hypothesis of nonlinear systemic risk contributions, e.g., the asymmetric responses of the banking system to an adverse shock to a bank, by not only different magnitudes of the responses but also the changing in response directions across regimes. Second, the systemic risk contributions measured by  $\Delta RSCoVaR$ stochastically dominate (systemically riskier than) those measured by  $\Delta CoVaR$ . This result raises the concern about a underestimation of systemic risk contributions by  $\Delta CoVaR$ , which has found 136 basis points on average less than those measured by  $\Delta RSCoVaR$  in terms of the percentage losses of asset values. Third, the dominating banks are generally those that are ranked the highest in terms of the systemic risk contributions. Moreover, from policy and regulatory perspectives, it is important to see in this paper that the identification and the ranking of the SIFIs remain consistency across subsamples considered in this paper. In addition, the systemic risk contributions estimated from the 2007 to 2009 crisis period are systemically riskier than those from the prior- and post-crisis subsamples. This significant time-variation in systemic risk contributions thus supports the modeling of risk structure changes in tails. Last but not least, the panel data regressions show that BHCs' characteristics and housing price significantly accumulate systemic risk in the background of recent asset boom. Particularly, the predictive variables of *leverage* and housing price generate the highest negative relationship among competing measures between contemporaneous and forward –  $\Delta RSCoVaR$  at 4- and 8-quarter horizons. In this regard, macroprudential regulation can favorably be countercyclical based on the proposed regime-switching systemic risk measure.

The rest of this paper is structured as follows. Section 2 briefly describes the existing *CoVaR* approach of Adrian and Brunnermeier (2016). Section 3 motivates the importance of modeling nonlinearities in systemic risk measure, followed by generalizing the  $\Delta CoVaR$  approach to allow regime shifts in tails as  $\Delta RSCoVaR$ . Several testable distress scenarios are also illustrated using  $\Delta RSCoVaR$ . Section 4 identifies and ranks systemically important financial institutions by testing five null hypotheses using the significance and stochastic dominance tests of Bernal et al. (2014) and Castro and Ferrari (2014). Section 5 reports the empirical results for stress-testing large bank holding companies in the U.S. The focus in this section is particularly given to identifying SIFIs and ranking the identified SIFIs. Moreover, the asymmetric systemic risk measure of Lopez-

 $<sup>^4</sup>$  A mean-reversion effect on the banking system in this context indicates that if a bank is not systemically important, the banking system digests the bank's materialized risk with the adjustment back towards the system equilibrium.

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