ADBI Working Paper Series

MEASURING SYSTEMIC RISK CONTRIBUTION OF INTERNATIONAL MUTUAL FUNDS

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No. 594
September 2016

Asian Development Bank Institute

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The authors thank Ilhyock Shim and participants at the ADBI workshop for useful comments and suggestions.

Suggested citation:

Aizenman, J., Y. Jinjarak, and H. Zheng. 2016. Measuring Systemic Risk Contribution of International Mutual Funds. ADBI Working Paper 594. Tokyo: Asian Development Bank Institute. Available: https://www.adb.org/publications/measuring-systemic-risk-contribution-international-mutual-funds/

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Abstract

This study provides new evidence of systemic risk contribution in the international mutual fund sector from 2000–2011. The empirical analysis tracks the systemic risk of 10,570 mutual funds investing internationally. The main findings suggest that the systemic risk contributions of international mutual funds are more than proportional given the fund's size. Policy implications are discussed in terms of practicality of regulation, macroprudential approach, and risk-taking behavior of fund managers.

JEL Classification: E44, F3, G15

Contents

1. INTRODUCTION

The global financial crisis of 2007–2009 has increased the attention of policymakers and academics on the scale and operation of interconnected financial systems, especially on what has become known as "too big to fail" in the global financial system. The designation of "systemically important financial institution" has recently extended to cover both banks and non-banks.[1] In this research, we study the systemic risk of the mutual fund sector in the global financial system. At the end of 2012, total net assets under management of mutual funds stood at US$26.8 trillion, accounting for more than 50% of global market capitalization.[2] Subject to redemptions, mutual funds may be faced with liquidity and financial market runs, thereby rendering the mutual fund sector too big to fail.[3] In this vein, we offer new evidence on systemic risk contribution based on mutual fund characteristics, investment performance, as well as their intertwining empirically.

Our measure of systemic risk contribution is a difference between systemic risk of the mutual fund sector (henceforth, systemic risk) conditional on mutual fund i being in distress (performance base, i.e., investment return) vis-à-vis systemic risk of the mutual fund sector conditional on mutual fund i being in normal state; henceforth $\Delta CoVaR$ (Adrian and Brunnermeier 2011). The estimation of systemic risk contribution is done in three stages. Firstly, value at risk (VaR) is estimated for fund i using quantile regression. Secondly, systemic risk conditional on mutual fund i being in distress as well as systemic risk conditional on mutual fund i being in normal state, are estimated from fund-specific VaR. Thirdly, $\Delta CoVaR$ is calculated.

Applying $\Delta CoVaR$ to weekly data of 10,570 mutual funds from October 2000 to June 2011, we track the systemic risk of mutual funds globally. The findings shed light on possible channels of global risk transmission through mutual funds, i.e., fire sales by distress funds holding common assets, market sentiment driven by fund flows, and active portfolio management transmitting shocks across markets.[4]

Our paper contributes to a growing literature on granularity in macroeconomics (Gabaix 2011). Jinjarak and Zheng (2014) provided related evidence on what would have been the pattern of risk if, say, regulations would have capped the size of funds at a ceiling that would have eliminated the top 20. The rest of this paper is organized as follows. Section 2 reviews the methodology of estimating the time-varying systemic risk contribution $\Delta CoVaR$. Section 3 describes the data and the summary statistics of these risk measures. Section 4 discusses the implications. Section 5 concludes.

[1] The Economist (2012) discussed relevant rules brought on by regulators in the United States, expanding to insurers, asset management funds, private equity firms, hedge funds, and mutual funds.

[2] Investment Company Institute (5 April 2013).

[3] On liquidity and financial market runs, and the role of international investors in crisis, see, for instance, Bernardo and Welch (2004) and Manconi, Massa, and Yasuda (2012).

[4] See, for example, Ben–Rephael, Kandel, and Wohl (2012); Jotikasthira, Lundblad, and Ramadorai (2012); Coval and Stafford (2007); Baker, Wurgler, and Yuan (2012); Raddatz and Schmukler (2011); Broner, Gelos, and Reinhart (2006); Goldstein and Pauzner (2004); and Kaminsky, Lyons, and Schmukler (2001).

2. ESTIMATION OF SYSTEMIC RISK CONTRIBUTION

2.1 Definition of $CoVaR$ and $\Delta CoVaR$

Let R_i be the return variable for mutual fund i, and VaR_i the value at risk (VaR) that measures the individual risk of fund i. For a given probability q, the tail risk VaR_i^q equals the negative value of the qth quantile of R_i:

$$\Pr\left(R_i \leq -VaR_i^q\right) = q. \tag{1}$$

Essentially, VaR represents a loss percentage and is conventionally reported as a positive number. Eq.(1) follows such sign convention:[5] the greater VaR_i^q is, the riskier fund i is. Denote R_{system} as the return of the global mutual fund sector, which is calculated as the total net assets (TNA)-weighted return of all funds in the sample. Based on Adrian and Brunnermeier (2011), the conditional systemic risk, $CoVaR^q_{system|\mathbb{C}(R_i)}$, is defined as the VaR of the global mutual fund sector contingent on fund i being in state $\mathbb{C}(R_i)$:

$$\Pr\left(R_{system} \leq -CoVaR^q_{system|\mathbb{C}(R_i)} \middle| \mathbb{C}(R_i)\right) = q. \tag{2}$$

The conditional systemic risk, $CoVaR^q_{system|\mathbb{C}(R_i)}$, is calculated as the negative value of qth quantile of R_{system} conditional on state $\mathbb{C}(R_i)$. Two financial states are of interest: the distress state, with fund i being at risk such that $R_i = -VaR_i^q$, and the median state, with $R_i = -VaR_i^{50\%}$. The systemic risk contribution of fund i to the global mutual fund sector, $\Delta CoVaR^q_{system|i}$, is defined as the difference between the systemic risk conditional on fund i being in distress and the systemic risk conditional on fund i being in the median state:

$$\Delta CoVaR^q_{system|i} = CoVaR^q_{system|R_i=-VaR_i^q} - CoVaR^q_{system|R_i=-VaR_i^{50\%}}. \tag{3}$$

This way $\Delta CoVaR^q_{system|i}$ captures the risk transmitted from fund i to the global mutual fund sector. However, it does not differentiate whether the systemic risk contribution is driven by the idiosyncratic risk of fund i or by common factors that affect every fund simultaneously. Such a property enables us to analyze how systemic risk responds to internal dynamics and exogenous shocks. If the systemic risk contribution measured in such a broad way turns out to be low, it suggests the risk of these funds is unlikely to be harmful to the whole sector. If, however, the systemic risk contribution is high, exploring its origins is useful for imposing regulations.

2.2 Estimation of $CoVaR$ and $\Delta CoVaR$

To capture the time variation in the joint distribution of R_{system}, the return of the mutual fund sector, and R_i, the return of mutual fund i, we follow Adrian and Brunnermeier (2011) to estimate the conditional distribution as a function of various state variables.

[5] A negative VaR means that the fund may still make a profit even when the rare adverse event happens. For example, for a fund with US$1 under management, a $VaR_{5\%}$ of -0.1 means that the fund has a 5% chance of making a profit of less than US$0.1 or a 95% chance of making a profit of more than US$0.1.

Specifically, we run the following qth quantile regression conditional on a vector of lagged state variables M_{t-1}:

$$R_{i,t} = \alpha_i + \gamma_i M_{t-1} + \varepsilon_{i,t}, \tag{4}$$

$$R_{system,t} = \alpha_{system|i} + \beta_{system|i} R_i + \gamma_{system|i} M_{t-1} + \varepsilon_{system|i,t}, \tag{5}$$

where M_{t-1} includes the return of the Morgan Stanley Capital International (MSCI) World Index ($R_{\mathrm{MSCI\_Global}}$), the difference between the 3-month and overnight London Interbank Offered Rate (LIBOR) ($LIBOR_{\mathrm{3m-o/n}}$), the difference between the overnight LIBOR and the federal funds target rate ($LIBOR_{\mathrm{o/n}} - FFTarget$),[6] the difference between the Chicago Board of Trade's (CBOT) federal funds futures rate and the 3-month treasury rate ($FFFutures - Tbill_{\mathrm{3m}}$), the difference between federal funds futures rate and federal funds target rate ($FFTarget - FFFutures$),[7] and the return of the Chicago Board Options Exchange Volatility Index (ΔVIX).

While the ordinary least square estimates the coefficients by minimizing the sum of the squared residuals, the quantile regression finds the solution by minimizing the sum of the absolute residuals weighted by the quantile (Koenker and Bassett 1978). In the qth quantile regression, the conditional quantile of the error term $\varepsilon_{i,t}$ and $\varepsilon_{system|i,t}$ satisfy that $Q(\varepsilon_{i,t}|M_{t-1}) = 0$ and $Q(\varepsilon_{system|i,t}|R, M_{t-1}) = 0$. Such specifications allow us to estimate the coefficients consistently even if the data is not Gaussian distributed.

The time-varying tail risk of fund i, $VaR_{i,t}^q$, is calculated as the negative of the predicted value from the qth quantile regression based on Eq.(4):

$$VaR_{i,t}^q = -(\hat{\alpha}_i + \hat{\gamma}_i M_{t-1}),$$

where $\hat{\alpha}_i$ and $\hat{\gamma}_i$ are the estimated coefficients from the quantile regression based on Eq.(4). The systemic risk of the global mutual fund sector conditional on fund i being in distress, $CoVaR_{system|i}^q$ (or $CoVaR_{system|R_i=-VaR_i^q}^q$), is computed as the negative of the predicted value from the qth quantile regression based on Eq.(5), conditional on the individual fund being in distress ($R_{i,t} = -VaR_{i,t}^q$) such that

$$CoVaR_{system|i}^q = -[\hat{\alpha}_{system|i} + \hat{\beta}_{system|i}(-VaR_{i,t}^q) + \hat{\gamma}_{system|i} M_{t-1}].$$

Following from Eq.(3), the time-varying systemic risk contribution of fund i is given by

$$\Delta CoVaR_{system|i,t}^q = \hat{\beta}_{system|i}(VaR_{i,t}^q - VaR_{i,t}^{50\%}).$$

Estimating qth quantile regressions based on Eqs.(4) and (5) for every mutual fund in our sample, we obtain panel data of weekly $VaR_{i,t}^q$, $CoVaR_{system|i}^q$, and $\Delta CoVaR_{system|i,t}^q$. The parameter q typically takes a value of 1% or 5% in practice.

[6] See Hamilton (2008) who distinguished between $LIBOR_{3m-o/n}$ and $LIBOR_{o/n} - FFTarget$ as liquidity premium and risk premium.

[7] See Kuttner (2001) for the decomposition of the monetary policy change into expected and unexpected components. The methods are relatively practical and efficient in capturing the market's response to monetary policy; see also Bernanke and Kuttner (2005) and Wongswan (2009).

We choose $q = 1\%$.[8] as the default value in the following estimations and drop the superscript q from these variables in the remaining part of this paper.

3. DATA AND SUMMARY STATISTICS

3.1 Data

The weekly fund-level data are from Emerging Portfolio Fund Research (EPFR). The sample covers equity funds investing in both developed and emerging markets from 20 October 2000 to 8 June 2011 (554 weeks). Key fund characteristics include total net assets (TNA) under management, investment flows measured as a ratio to TNA, and returns calculated as the weekly change in net asset value (NAV) divided by the NAV of the previous week. The data used to construct state variables (MSCI world index, 3-month and overnight LIBOR, federal funds target rate, CBOT's federal funds futures rate, and VIX) are obtained from Datastream and Bloomberg.

The fund data is screened in standard procedures following Coval and Stafford (2007) and Jotikasthira, Lundblad, and Ramadorai (2012). First, we exclude funds with TNAs of less than US$5 million throughout the sample period. Second, we drop funds with investment flows or returns falling out of the range $[-50\%, 200\%]$..[9] Third, we keep only funds with a total number of observations of more than 30 weeks. The final sample includes 1,574,254 fund weeks, covering 10,570 distinct funds investing worldwide.

3.2 Summary Statistics

Table 1 reports the summary statistics of 10,570 funds over 554 weeks. Both the mean and the standard deviation of the individual fund's return R_i are larger than that of the mutual fund sector's return R_{system}. The risk of the individual fund VaR_i is higher and more volatile than that of the systemic risk VaR_{system}. The average $CoVaR_{system|i}$ (the systemic risk conditional on the individual fund being in distress) is greater than the average VaR_{system} (the unconditional systemic risk measure).[10] This difference together with the nontrivial systemic risk contribution $\Delta CoVaR_{system|i}$ suggests that financial distress at the individual fund level contributes to the systemic risk of the global mutual fund sector.

In order to study the individual fund's systemic risk contribution, we will focus primarily on $\Delta CoVaR$ in the following. The left panel of Figure 1 plots the time-series average of the $\Delta CoVaR$ (y-axis) against VaR (x-axis) using all 10,570 funds in the sample. It shows that the individual risk VaR is positively related to its systemic risk contribution $\Delta CoVaR$. The two variables have a correlation coefficient of 0.35. They are not only correlated cross sectionally but over time. Focusing on the cross-sectional average of $\Delta CoVaR$ and VaR for the top 20% largest funds indicates that the two variables exhibit strong co-movement in their time series, as shown in the right panel of Figure 1. Their correlation coefficient is as high as 0.9.

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[8] The estimates using $q = 5\%$ do not alter our main results and are available upon request.

[9] There are 9 fund weeks with returns falling out of the range $[-50\%, 200\%]$ in the initial raw sample (before restricting the TNA to be more than US$5 million. Imposing constraints on flows and returns efficiently filters out fund weeks at the early stage of establishment and at the time of exit, when the data is relatively noisy.

[10] The estimation coefficients on the macro state variables based on Eqs.(4) and (5) are reported in the Appendix.

Table 1: Summary Statistics

Variable	Mean	SD	Minimum	Maximum	Observations
R_i	0.15	3.14	–45.99	142.22	1,574,254
R_{system}	0.13	2.39	–15.66	8.08	554
VaR_i	6.09	3.31	–10.81	89.96	1,571,795
VaR_{system}	2.42	2.65	–8.08	36.48	554
$CoVaR_{system\|i}$	6.55	2.89	–8.03	58.94	1,571,795
$\Delta CoVaR_{system\|i}$	4.26	2.10	–18.99	44.06	1,571,795

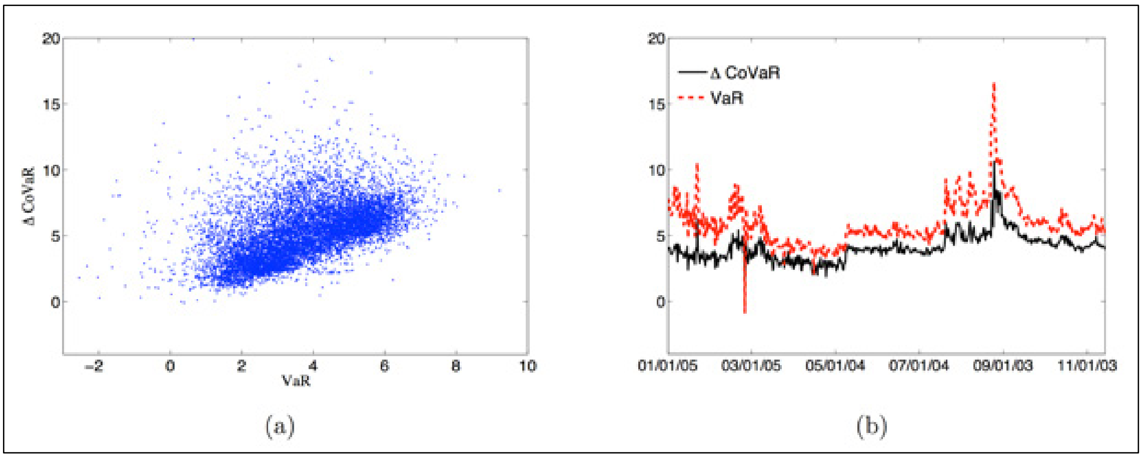
SD = standard error.

Notes: R_i is calculated as the NAV return of the individual fund and R_{system} is the TNA-weighted total return of all funds in the sample. VaR_i and VaR_{system} are the value at risk of individual fund and the whole mutual fund sector, which equals the negative of the 1% quantile of R_i and R_{system} respectively. $CoVaR_{system|i}$ is the systemic risk conditional on the individual fund being in financial distress. $\Delta CoVaR_{system|i}$ measures the contribution of individual risk to the systemic risk. All summary statistics except for observations are reported in percentages.

Source: Compiled by the authors.

Unlike the risk within the banking industry documented in Adrian and Brunnermeier (2011), the observed cross-sectional and time-serial correlation suggest that a fund's VaR is informative in forecasting its systemic risk contribution $\Delta CoVaR$. It seems to suggest that regulation based on the individual fund's risk could be useful. Nonetheless, this forecasting power of VaR on $\Delta CoVaR$ is not perfect. As shown in the left panel of Figure 1, there are a small number of funds with positive VaR but negative $\Delta CoVaR$, suggesting the financially distressing conditions of these funds have the opposite effect on the systemic risk of the whole mutual fund industry. However, these outliers account for only 0.4% of asset under management. To be prudent in evaluating the systemic importance of the individual fund, we rely on $\Delta CoVaR$ which covers the systemic risk contribution arising from both internal dynamics and exogenous shocks.

Figure 1: The Relation between ΔCoVaR and VaR from 2001 to 2011



Notes: The left panel plots the time-series average of $\Delta CoVaR$ for each of the 10,570 funds in our sample against their time-series average VaR. The right panel plots the cross-section average of _ $\Delta CoVaR$ and VaR for the top 20% largest funds. Both $\Delta CoVaR$ and VaR are reported in percentages.

Source: Compiled by the authors.

3.3 Persistence of $\Delta CoVaR$

At the beginning of each week, we sort all mutual funds in ascending order according to their estimated $\Delta CoVaR$. Based on this ranking, we group the funds into five quintile portfolios, with quintile 1 (Q1) funds having the smallest $\Delta CoVaR$, i.e., systemically safe funds, and quintile 5 (Q5) funds having the largest $\Delta CoVaR$, i.e., systemically risky funds. Table 2 reports the probability of fund transiting from $\Delta CoVaR$ quintile i in period t to quintile j in period $t+1$. The reported probability is calculated as the total number of funds switching from quintile i into quintile j in period $t+1$ divided by the total number of funds in quintile i in period t. To account for possible survival bias, the probability of funds dropping from the sample in period $t+1$ is reported in the column titled Attrition Rate. The diagonals reflect the probability of the funds staying in the same quintile in the subsequent week. Evidently, funds tend to remain in the same $\Delta CoVaR$ quintile over the sample period. This persistence is especially the case at the tail ends for Q1 (systemically safe) funds and Q5 (systemically risky) funds.

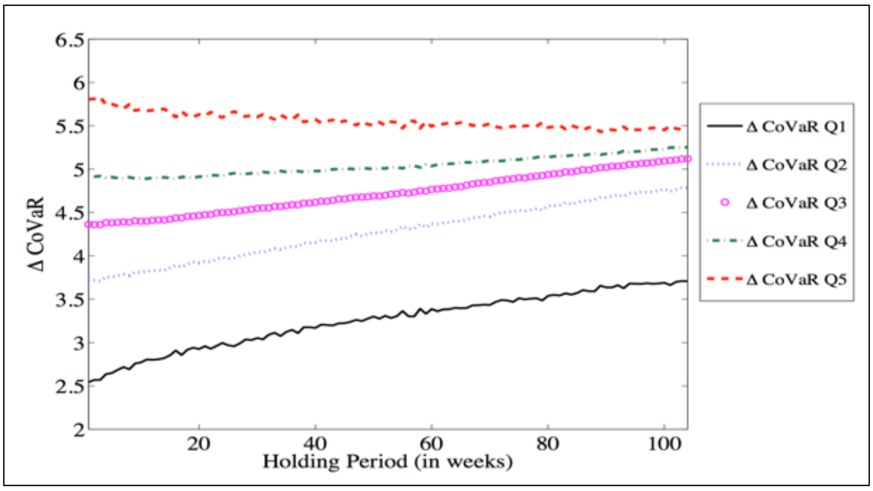
Table 2: Transition Matrix

Current	Subsequent ΔCoVaR Quintile					
$\Delta CoVaR$ Quintile	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Attrition Rate**
Q1	67.1	19.5	6.1	3.0	1.7	2.6
Q2	19.1	44.7	21.5	8.8	4.0	1.9
Q3	5.9	21.5	40.3	22.4	8.1	1.9
Q4	3.0	8.4	22.5	43.6	20.7	1.8
Q5	1.9	4.1	7.8	20.6	63.8	1.8

Notes: This table reports the probability for funds in $\Delta CoVaR$ quintile i in period t to switch to $\Delta CoVaR$ quintile j in period $t+1$. Each cell value is calculated as the total number of funds transiting from quintile i to quintile j in period $t+1$ divided by the total number of funds in quintile i in period t. The probability of funds dropping from the sample at $t+1$ is reported in the column "Attrition Rate" to account for survival bias.

Source: Emerging Portfolio Fund Research and author's calculation.

Figure 2: Persistence of $\Delta\mathrm{CoVaR}$



Notes: At the start of week *t,* all funds are sorted into five quintile portfolios based on the ascending ranks of $\Delta CoVaR$. Based on the quintile portfolios formed in week t, we plot their mean $\Delta CoVaR$ in week t+k, for k = 0, . . . , 104.

Source: Emerging Portfolio Fund Research and author's calculation.

The persistence of systemic risk contribution $\Delta CoVaR$ decays slowly over time.[11] Figure 2 tracks the equal-weighted average $\Delta CoVaR$ of the quintile portfolios over 104 weeks (approximately 2 years) after their formation. Although the difference shrinks gradually, the $\Delta CoVaR$ is consistently higher in week $t+k$ ($k=1,\ldots,104$) for a portfolio that is systemically riskier in week t.

4. DISCUSSION

The estimated systemic risk contribution is useful in studying other aspects of mutual fund investment internationally. For instance, we can examine whether funds with higher systemic risk contribution have higher investment flows and returns in the tranquil period and lower investment flows and returns in the panic period. Further, it will be interesting to see if the impacts of systemic risk contribution on investment flows and returns are regime-dependent. On evaluating the determinants of systemic risk contribution, one can study whether larger funds leads to higher systemic risk contribution and the fund size effect is particularly pronounced during the panic period.

Moreover, the systemic risk measure can be used to study whether there is a nonlinear relation between the mutual funds' prospective performance and their systemic risk contribution. Funds with more negative prospective flows (prospective outflows) should be associated with lower systemic risk contribution. The outflows reduce fund size and therefore its systemic importance. On the other hand, expecting significant outflows, fund managers may become cautious with their investment, i.e., holding more liquid assets that can be quickly sold, which reduces the fund-specific risk and therefore systemic risk contribution. The nonlinear relationship may imply that higher prospective flows result in lower systemic risk contribution if the prospective flows are large enough. This possibility may be driven by fund managers' intention to maintain stable flow streams that keep the flow volatility low and improve fund performance (Rakowski 2010).

In addition, any nonlinear relation between prospective returns and systemic risk contribution may indicate that worse prospective returns lead to lower systemic risk contribution when the prospective returns are relatively low. The prospective returns may motivate the mutual fund managers to deliberately reduce their choice of risk over time (Brown, Harlow, and Starks 1996; Chevalier and Ellison 1997, 1999; Kempf and Ruenzi 2008; Kempf, Ruenzi, and Thiele 2009; Chen and Pennacchi 2009; Huang, Sialm, and Zhang 2011), and therefore the systemic risk contribution. As summarized in Kempf, Ruenzi, and Thiele (2009), mutual fund managers have the compensation incentive to compete for more investment flows and higher returns by increasing their risk levels, and the employment incentive to keep risk low in order to maintain the liquidity and the safety of their asset holdings. When prospective returns are sufficiently negative, funds are expected to suffer from large investment outflows. If fund managers increase their risk further, the probability of fire sales is likely to be high, and their occurrence further distresses fund performance and threatens fund managers' job security. In such a situation, the employment incentive is likely to dominate the compensation incentive. When the prospective returns are relatively high, higher prospective returns are associated with lower systemic risk contribution. Kempf and Ruenzi (2008); Kempf, Ruenzi, and Thiele (2009); Brown, Harlow, and Starks (1996); and Chevalier and Ellison (1997) found that outperforming funds reduce their

[11] See Santa-Clara and Yan (2010) for more evidence of risk persistence.

subsequent risk.[12] It is likely that the employment incentive dominates the compensation incentive when the returns are sufficiently positive, as fund managers are more concerned about their career and reputation (Kempf, Ruenzi, and Thiele 2009). Therefore, they tend to act prudently to maintain a consistent performance record and keep their investment safe, rather than trying to improve their performance further. Such incentives for choosing risk at the fund level seem to apply in the variation of systemic risk contribution.

Limitations of our systemic risk measure on international mutual funds are in order. First, this measure may not fully differentiate whether systemic risk contribution is driven by idiosyncratic risk or common factors. Therefore, it is difficult to impose regulation calibrated on a factor. Under efficient markets, co-movements of financial institutions' risk measures should convey information on both direct and indirect linkages across financial institutions (IMF 2009). Second, here mutual fund is in distress when return is low or negative. Given that mutual funds have no explicit leverage, it is a challenge to justify or motivate the "distress" of a mutual fund. Several possibilities include, for instance: severe and persistent redemptions may be a better sign of distress for an open-ended fund; low absolute return or under-performance against the benchmark; and aversion to be the worst performer among the peers may matter more. Third, it remains to be seen whether the absolute size of a fund matters in practice. In terms of the impact on asset prices and systemic risk, a more meaningful factor may be the presence of a fund active in a specific market compared to the size/liquidity of the asset market (big fish in a small pond). An even more important aspect is correlation across mutual funds due to clustering of investor flows and fund managers' purchase and/or sale of assets as well as common use of a benchmark. Even though individual funds or individual investors are small in size, when they move in the same direction their market impact will be large (Miyajima and Shim 2014); also redemption-driven sales and fund manager sales are positively correlated (Shek, Shim, and Shin 2015). This implies a macroprudential approach is more important than a microprudential approach on individual funds' risks. Fourth, our findings are squared with an IMF study (albeit with smaller number of funds). IMF GFSR (2015) used Adrian and Brunnermeier's (2011) CoVaR and ran quantile regressions on about 1,500 funds investing in different asset classes. The study found that funds' contribution to systemic risk depends more on their investment focus (that is, asset class) than on their size; the average contribution to systemic risk does not increase with a fund's parent company's size.

5. CONCLUSIONS

We offer new evidence of systemic risk contribution in the international mutual fund sector from 2000 to 2011. Our analysis of 10,570 funds tracks the systemic risk of the global mutual fund sector that can increase from financial distress at the fund level. Empirically, the systemic risk contributions of international mutual funds, be they originated from idiosyncratic risks and/or common factors that affect the mutual fund industry, are found to be more than proportionally larger given the fund's size.

[12] Kempf, Ruenzi, and Thiele (2009) found that low-performing mutual fund managers tend to increase risk to increase compensation when the market condition is good and to reduce risk to secure their job when the market condition is poor. Schwarz (2012) adjusted for the sorting bias in Kempf, Ruenzi, and Thiele (2009) and found that underperforming managers tend to increase risk subsequently regardless of the market condition.

Possible extensions can be built on the estimated systemic risk contribution. We can derive potential implications on investment performance of the mutual fund sector, focusing on systemically important mutual funds vis-à-vis the others. It will be useful to examine whether systemic risk contribution is negatively (positively) associated with net investment inflow and return performance in a crisis (non-crisis) period. The extension can also study any non-linear relationship between systemic contribution and prospective net investment inflows and return performance. Further, while the size of the mutual fund drives systemic risk contribution, the effect may be more than proportionally larger for systemically important funds, especially during panic periods in the financial markets.

For the past decade, total net assets of mutual funds investing in Asia and the Pacific have been around US$3 trillion, equivalent to more than 10% of worldwide total net assets of mutual funds.[13] To put this number into perspective, the investment is more than a third of the People's Republic of China's gross domestic product (GDP), Japan's GDP, or twice the size of the Republic of Korea's GDP. The global financial crisis is a watershed event for monetary authorities and regulators to take preemptive action on the financial sector. Understanding systemically important financial institutions and their investment patterns should be the prerequisite for policy implementation.

[13] In this paper, Asia and the Pacific covers Australia; the People's Republic of China; Hong Kong, China; India; Japan; the Republic of Korea; New Zealand; Pakistan; the Philippines; and Taipei,China.

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APPENDIX

State Variable Coefficients from 1% Quantile Regressions

Variables	R_i	R_{system}	R_{system}
R_i			0.44***
			(150.76)
$R_{MSCI\ Global}$	–1.52***	2.82	0.15
	(–5.19)	(0.15)	(0.47)
$LIBOR_{3m-o/n}$	–4.04***	–3.21**	–2.30***
	(–62.23)	(–2.12)	(–91.76)
LIBORo/n − FFTarget	–5.24***	–3.27	–2.67***
	(–50.20)	(–1.52)	(–96.71)
FFFutures − Tbill3m	0.90***	0.26	0.59***
	(16.95)	(0.16)	(25.54)
FFTarget − FFFutures	–9.96***	–5.58***	–4.95***
	(–124.86)	(–3.32)	(–84.85)
∆VIX	–6.08***	–1.77	0.06
	(–32.15)	(–0.41)	(1.11)
Constant	–5.79***	–4.32***	–2.90***
	(–237.75)	(–7.50)	(–309.85)
Observations	1,571,795	545	1,571,795
Pseudo R^2	0.272	0.367	0.555
Number of funds	10,570		10,570

Notes: The first column reports panel 1% quantile regression of individual fund return R_i on lagged state variables using the panel data of all fund weeks. The second column reports 1% quantile regression of system return R_{system} on lagged state variables. The third column reports panel 1% quantile regression of R_{system} on lagged state variables and R_i. The t-statistic is reported in the parenthesis below the corresponding coefficient.

Source: Emerging Portfolio Fund Research and author's calculation.