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Köksal, Bülent and Orhan, Mehmet

Central Bank of Turkey, Fatih University - Department of Economics

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Market Risk of Developed and Developing Countries During the Global Financial Crisis*

Bülent Köksal † and Mehmet Orhan ‡

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Abstract: This study compares the performance of the widely used risk measure Value-at-Risk (VaR) across a large sample of developed and developing countries. The performance of the VaR is assessed by both unconditional and conditional tests of Kupiec and Christoffersen, respectively, as well as the Quadratic Loss Function. Results indicate that the performance of VaR as a measure of risk is much worse for developed countries than the developing ones during our sample period. One possible reason might be the deeper initial impact of global financial crisis on developed countries than emerging markets. Results also provide evidence of decoupling between emerging and developed countries in terms of market risk during the global financial crisis.

JEL Classification Codes: C32; C51; G01; G32.

Keywords: Value-at-Risk (VaR), Developed Countries, Emerging Markets, ARCH/GARCH Estimation, Kupiec Test, Christoffersen Test, Quadratic Loss Function.

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† Corresponding author, Central Bank of Turkey, Istiklal Cad. 10, Ulus, 06100 Ankara, Turkey.
Tel: +90 312 507 5899. E-mail: bulent.koksal@tcmb.gov.tr.
‡ Department of Economics, Fatih University, Istanbul, Turkey. Tel: +90 212 866 33 00, Ext: 5012.
E-mail: morhan@fatih.edu.tr.

1. Introduction

Risk management has become even more crucial after the 2007-2009 global financial crisis that hit the world economy.[1] The risk will be reflected in the risk premium which is determined by the repayment capability of the borrower. Each borrower has to pay the "risk premium" based on his perceived risk. It is surprising to note that several developed countries are influenced from the crisis more adversely than the emerging market economies as reflected by the Credit Default Swap (CDS) rates (see Figure 1).

[Insert Figure 1]

It is interesting that the firms with expertise in risk management have collapsed while or after the global financial crisis.[2] Mismanaged risk together with technological advances in the financial sector contributed to the global financial crisis. A special report published by the European Commission (2009) that examines the anatomy of the crisis states that "The crisis was preceded by long period of rapid credit growth, low risk premiums, abundant availability of liquidity, strong leveraging, soaring asset prices and the development of bubbles in the real estate sector. Over-stretched leveraging positions rendered financial institutions extremely vulnerable to corrections in asset markets. As a result a turn-around in a relatively small corner of the financial system (the US subprime market) was sufficient to topple the whole structure." Many of the countries had to support their financial intermediaries because of the toxic assets in their balance sheets with significantly lower values.[3] The cost of dealing with the consequences of the crisis created huge budget deficits and contributed to the low economic growth not only in small EU countries like Greece, Ireland, but also in more

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[1] For an analysis of the crisis with respect to its different dimensions, see the special issues of the Journal of International Money and Finance (Volume 28, Issue 8, 2009) on "The Global Financial Crisis: Causes, Threats and Opportunities", the Journal of International Economics on "The Global Dimensions of the Financial Crisis" (forthcoming) and the Journal of Asian Economics (Volume 21, Issue 3, 2010) on "The Financial Crisis of 2008-09: Origins, Issues, and Prospects".

[2] For a list of acquired or bankrupt banks in the 2007-2009 global financial crisis, see http://en.wikipedia.org/wiki/List_of_acquired_or_bankrupt_banks_in_the_late_2000s_financial_crisis (retrieved on March 20, 2012). See Tett (2009) for a detailed overview of AIG's collapse.

[3] Toxic or troubled assets are the securities that suffer extreme illiquidity and difficult to value.

advanced economies like Spain, Italy and the UK. Basel II Accord provided guidelines in terms of capital requirements for a sound banking system but it was heavily criticized for boosting procyclicality of the banking sector.[4] In response, the Basel Committee on Banking Supervision established revised global standards, known as Basel III.

VaR (Value-at-Risk) is devised as unit free risk measure which is very convenient for practical purposes. In its simplest form it is defined as the maximum expected loss of a portfolio at the given confidence level and holding period. VaR became more popular especially due to its simplicity (Giot and Laurent (2004)). As Berkowitz and O'Brien (2002) put "Value-at-Risk has become a standard measure of financial market risk that is increasingly used by other financial and even non-financial firms as well." Its popularity increased after Bank for International Settlements and SEC address VaR as a measure to quantify risk as well as Basel Committee on Banking Supervision's (1994, 1996) imposition of VaR use on financial institutions. The use of VaR in assessing risk is not limited to financial markets only. Giot and Laurent (2003), for instance, make use of ARCH to calculate VaR in commodities markets of aluminum, copper, nickel, and Brent crude oil. Naïve methods like variance-covariance and historical simulation could not survive because of their considerable shortcomings and there is a remarkable progress in computing more accurate VaR but in the expense of more complicated and sophisticated computation techniques that require more effort and time. Advances in the information technology enabled investors to perform VaR estimations that were not possible two decades ago.

This study compares the performance of the widely used Value-at-Risk (VaR) across a large sample of countries and provides evidence of decoupling between emerging and developed

[4] See Cannata and Quagliariello (2009) and Moosa (2010) for discussions. Goodhart (2008) describes the regulatory failings during the crisis.

countries in terms of market risk during the global financial crisis. Current literature about the decoupling finds that emerging countries were isolated from the developments in the U.S. financial markets at the beginning of the crisis but followed the rest of the developed countries afterwards in terms of their reaction to the worsening situation in the U.S. economy.[5] Our study contributes to this literature by providing evidence of decoupling from the perspective of Value-at-Risk.

The rest of the paper is organized as follows. Section 2 describes empirical methodology and data. Section 3 describes the tests to evaluate VaR and discusses the results while Section 4 concludes.

2. Empirical Methodology and Data

VaR is the maximum expected percentage loss possible at a given confidence level for some specified investment horizon. More technically, VaR ($1-\alpha$) is defined as the threshold that is exceeded 100*α times out of 100 trials on average. $1-\alpha$ is the confidence level where $\alpha \in$ (0,1) is a real number. The cases where ex-post portfolio returns are lower than VaR estimates are called violations. One main input to the VaR calculation is the confidence level, ($1-\alpha$). Once the confidence level is set, VaR must be calculated in such a way that the violations should be equal to 100*α. For instance, if one wants to have the 95% confidence level, then VaR must be computed in such a way that the loss worse than the VaR will be 5% of all cases on average. That is, percentage of the losses greater than the suggested VaR will be 5 times out of every 100 cases on average. Therefore, VaR is the unique number based on the time series under focus.

[5] See Akın and Kose (2008), Dooley and Hutchison (2009), Felices and Wieladek (2012), Fidrmuc and Korhonen (2010), Frank and Hesse (2009), Kim et al. (2011), Kose et al. (2008), Saadi Sedik and Williams (2011), Uckun and Doerr (2010) and “The decoupling debate”, *The Economist*, Mar 6th 2008.

The second input that is necessary to calculate VaR is the standard deviation or volatility of the returns. Modeling and forecasting volatility is crucial for investors who are interested in the forecast of the variance of a time-varying portfolio return over the *holding period* to calculate VaR. The long-run forecast of the unconditional variance would be irrelevant for these investors who hold the asset for a certain period only. In a seminal paper, Engle (1982) shows how to model the conditional variance of a time series. Bollerslev (1986) generalizes Engle's work by allowing the conditional variance to be an ARMA process. These models are called GARCH (**G**eneralized **A**uto**r**egressive **C**onditional **H**eteroskedasticity) models.[6] Most recent and advanced VaR methods make use of GARCH models to calculate the conditional standard deviation.[7]

One issue that has to be addressed is to determine the specific GARCH model to estimate the conditional standard deviation since there have been quite a few models discussed in the literature. In his "Glossary to ARCH (GARCH)", Bollerslev (2008) lists more than 100 entries. In a related work, Orhan and Köksal (2012) compare the performances of 16 different GARCH specifications for calculating VaR using the same data and sample period as the ones used in this study. Accordingly, we use the conditional variance model selected by that study as the best model which is the simple ARCH model with one lag where the errors follow the t distribution.[8] Specifically, our model for calculating the conditional variance (and standard deviation) is as follows:

$$r_t = \mu_t + \varepsilon_t$$

$$\mu_t = \beta_0 + \beta_1 \varepsilon_{t-1}$$

[6] See Poon and Granger (2003) for an extensive survey.
[7] See, for example, Angelidis et al (2004), Ane (2006), Hartz et al (2006), and Fan et al (2008).
[8] GARCH model likelihoods are notoriously difficult to maximize. ARCH(1) model has the additional benefit of making convergences easier since the number of parameters to be estimated is smaller than other more complex models.

$$\varepsilon_t = \sigma_t v_t$$

$$Var(\varepsilon_t \mid I_{t-1}) = \sigma_t^2$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2$$

where $r_t = \ln(p_t / p_{t-1})$, p_t being the closing price of a country index (as described in the next section) at the end of day t, $\mu_t = E(r_t \mid I_{t-1})$ is the conditional mean, I_{t-1} denotes the information set available at time t-1 and v_t is a sequence of i.i.d. random variables with mean 0 and variance 1. We assume that v_t follow the standardized Student-t distribution which appropriately deals with the issue of fat tails of returns documented in the financial literature.

In this setting VaR is defined as:

$$\Pr(r_t < VaR(1-\alpha)) = \alpha$$

Once the conditional variance terms, $\hat{\sigma}_t^2$, are estimated, VaR is defined as:

$$VaR(1-\alpha) = \bar{r} - \hat{\sigma}_t t_\alpha$$

where $\bar{r}$ is the mean return, and t_α is the critical value of the t distribution with right-tail area α.

Although there are papers in the literature that calculate the VaR by utilizing GARCH models, to the best of our knowledge, this is the first study that compares the performance of VaR across a large sample of developed and emerging market economies by using data from the period that includes the recent global financial crisis.

We make use of the country indices for 44 developed and emerging market countries obtained from MSCI website.[9] This website describes the construction of the indices as “To construct a country index, every listed security in the market is identified. Securities are free float adjusted, classified in accordance with the Global Industry Classification Standard (GICS®), and screened by size, liquidity and minimum free float.” For each country, we use a total number of 1887 daily returns starting from May 30th, 2002 to August 24, 2009 to estimate the conditional standard deviations for VaR calculations using a 1000-day rolling window. Because of the rolling-window methodology that we employ, our final sample includes 888 estimated values of conditional standard deviations for the period March 30th, 2006 - August 24, 2009 which overlaps with the global financial crisis.[10] We calculate both in-sample and out-of-sample comparisons but report only the out-of-sample figures as the in-sample results are similar.

3. VaR as a Measure to Assess Market Risk

Basel Committee on Banking and Supervision asked for the implementation of VaR as well as the out-of-sample backtesting (Escanciano and Olmo (2011)). There are basically two approaches that use back-testing to compare the performance of VaR calculations in the finance literature. The “unconditional” approach does not take the sequence of violations into account. Using this approach, Kupiec (1995) defines the following test statistic that follows the χ^2 Distribution with 1 degree of freedom:

$$K = 2\ln\left(\left(1-\frac{F}{N}\right)^{N-F}\left(\frac{F}{N}\right)^{F}\right) - 2\ln\left((1-\alpha)^{N-F}(\alpha)^{F}\right)$$

[9] http://www.mscibarra.com/products/indices/international_equity_indices/gimi/stdindex/performance.html.
[10] Rolling-window methodology requires 44 countries × 888 = 39072 estimations in total.

where N is the total number of trials and F is the number of violations. If a method is perfect in returning the VaR figures, (F/N) will converge to α as suggested by the null hypothesis, H_0, and K will be approximately zero. In the opposite case, the difference between percentage of violations and α will be larger causing the test statistic to increase which means that the likelihood of null's rejection will be higher.[11] Kupiec Test assumes that the number of failures, F, follows the Binomial Distribution with parameters N and α. Based on the selected level of α, rejection of the Kupiec test's null hypothesis for a country implies that VaR is not very useful as a measure of market risk for that country.

Table 1, Panel A reports the Kupiec Test statistics for 5% and 1% significance levels as well as the proportion of violations for developed countries. Ideally, the proportion of violations should be approximately 0.1, 0.05, and 0.01, for VaR with 90%, 95%, and 99% confidence levels, respectively, and the Kupiec Test statistic should be close to 0. Panel B reports the number of rejections and non-rejections. Overall conclusion from Panel B is that # of rejections is much larger than the number of non-rejections implying that VaR as a measure of risk was not successful for developed countries during the crisis period.

[Insert Table 1]

The VaR methodology performed poorly particularly in Austria, Belgium, Canada, France, Italy, Norway, Spain and Sweden where the null hypothesis of the Kupiec test was rejected at all 90%, 95%, and 99% VaR confidence levels. VaR was a good measure of risk for Portugal, and Finland, followed by Singapore, Japan, and the USA.

[Insert Table 2]

Table 2, Panel A reports the performance of the VaR for developing countries. The null hypothesis was rejected at all significance levels for Hungary. There are slightly poor

[11] Percentage of violations being less or greater than α does not matter.

performances of VaR for Colombia, Israel, Mexico, Poland and Russia. Several developing countries including Korea, Malaysia, Morocco, Peru, Philippines, Thailand and Turkey have no rejections. It is possible to say that VaR has some value as measure of risk for Indonesia and for emerging market giants China, Brazil, and India. Table 2, Panel B reports the number of rejections and non-rejections for Kupiec test. Number of non-rejections is much larger than the number of rejections. A comparison of Panels B in Tables 1 and 2 clearly reveals that there was decoupling between emerging and developed countries in terms of market risk during the global financial crisis.

The two shortcomings of the Kupiec Test are that it does not take into account of the sequences of violations and it has limited power. To improve on the first shortcoming, Christoffersen et. al. (2001) design a test which gives emphasis to the predecessor of a violation. In case the violations are independent, the ratio of preceding violations and non-violations should not be significantly different.

If we define n_{ij} as the number of observations i followed by j $(i, j = 0{,}1)$ where 1 indicates a violation and 0 indicates a non-violation, then the test statistic

$$C = 2\ln\left(\frac{(1-\pi_{01})^{n_{00}}\,\pi_{01}^{n_{01}}\,(1-\pi_{11})^{n_{10}}\,\pi_{11}^{n_{11}}}{(1-\alpha)^{N-F}\,\alpha^{F}}\right)$$

where $\pi_{ij} = \dfrac{n_{ij}}{\sum_j n_{ij}}$, follows the χ^2 distribution with 2 degrees of freedom. If there is independence of the violations, then the numerator and denominator will be approximately same and the test statistic will be close to 0.

[Insert Table 3]

Table 3 reports the results from the Christoffersen Test for all countries. Note that the test rejects the appropriateness of VaR for Canada, Denmark, France, Greece, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, and UK at all levels of significance. Developing countries for which VaR performs poorly seem to be Colombia, Czech Republic, Hungary, India, Mexico, Morocco and Poland. The only country with non-rejections at all confidence levels is Turkey. Table 3, Panel B tabulates the number of rejections and non-rejections for the developed and developing countries separately. Overall conclusion from Table 3 is that the developing countries still have less rejections than the developed ones, but the difference is somewhat smaller when compared to the Kupiec test results reported Table 2 .

The last comparison we make is based on the Quadratic Loss (QL) function. Tests based on the number of rejections at different confidence levels give an idea about the performance of VaR as a measure of risk, but they do not take the magnitude of performance loss into account. Therefore, we make use of a loss function in order to assess the magnitude of the poor performance of the VaR. Define the QL (Quadratic Loss) function as:

$$QL_t = \begin{cases} 1+\left(r_t - VaR_t\right)^2 & if\ r_t < VaR_t \\ 0 & otherwise \end{cases}$$

for tth day's VaR. Since there were no convergences for some cases, we calculate the Average Quadratic Loss (AQL) for each country and for each VaR confidence level to make comparisons.

[Insert Table 4]

Next we rank countries based on these averages. Table 4, Panel A shows these ranks in parentheses just below the country names. Among the developed countries, Hong Kong has the minimum average quadratic loss followed by Finland, Portugal and Singapore. The highest average loss belongs to the securities markets of Norway, Canada and Italy. USA, Japan and Germany have relatively low AQLs.

Regarding the developing countries, the minimum AQLs belong to Israel and China followed by Colombia and Russia. The worst performing securities markets in terms of VaR as a measure of risk are Hungary, Poland, and Brazil. The VaR performs well for Russia and China but it performs poorly for Brazil and India.

Table 4 Panel B, reports the mean AQL for developed and developing countries at each VaR confidence level. The mean figures for developing countries are smaller than the ones for developed countries, providing some additional evidence for the decoupling discussed above.

4. Conclusion

This study examines the performance of Value-at-Risk (VaR) as a risk measure across a large sample of developed and emerging countries by utilizing unconditional and conditional tests of Kupiec and Christoffersen, respectively, and the Quadratic Loss Function. There are three main conclusions from our study. First, the performance of VaR as a risk measure was worse for developed countries than the developing ones during the global financial crisis. One possible reason might be that the developed countries have been affected from the crisis more adversely when compared to the emerging countries. Second, our results reveal some evidence of decoupling between emerging and developed countries in terms of market risk during the global financial crisis. Finally, as the rejection of the appropriateness of VaR for many countries indicates, alternative measures of risk should be used together with VaR and the performance of these risk measures should be regularly evaluated to improve the assessment of risks in a market. It would be interesting to see whether our conclusions continue to hold when other measures of risk together with different methodological choices are implemented.

References

Akın, Ç., and M.A. Kose. 2008. "Changing nature of North–South linkages: Stylized facts and explanations." Journal of Asian Economics 19, no. 1: 1-28.

Ane, T. (2006) " An analysis of the Flexibility of Asymmetric Power GARCH models" Computational Statistics and Data Analysis 51: 931-55.

Angelidis, T, Benos, A. , Degiannakis, S. (2004) "The Use of GARCH Models in VaR Estimation" Statistical Methodology 1: 105-128.

Basel Committee on Banking Supervision, 1994. Risk Management Guidelines for Derivates. Bank for International Settlements, Basel.

Basel Committee on Banking Supervision, 1996. Supplement to the Capital Accord to Incorporate Market Risks. Bank for International Settlements, Basel.

Berkowitz, J., and J. O'Brien. (2002). “How Accurate Are Value-at-Risk Models at Commercial Banks?” Journal of Finance 57, 1093-1111.

Bollerslev, T. (1986) "Generalized Autoregressive Conditional Heteroskedasticity." Journal of Econometrics 31: 307-27

Bollerslev, T. (2008) Glossary to Arch (Garch). CREATES Research Paper 2008-49.

Cannata, Francesco and Quagliariello, Mario, The Role of Basel II in the Subprime Financial Crisis: Guilty or Not Guilty? (January 14, 2009). CAREFIN Research Paper No. 3/09. Available at SSRN: http://ssrn.com/abstract=1330417

Chan, N.H., Deng, S-J., Peng, L. and Xia, Z., 2007. “Interval estimation of value-at-risk based on GARCH models with heavy-tailed innovations.” Journal of Econometrics 137, 556–576.

Christoffersen, P., Hahn, J., Inoue, A., 2001. “Testing and comparing Value-at-Risk measures.” Journal of Empirical Finance 8, 325–342.

Clark, E., Kassimitis, K., 2004. “Country financial risk and stock market performance: the case of Latin America.” Journal of Economics and Business 56 (2004) 21–41.

Dooley, M., and M. Hutchison. 2009. "Transmission of the U.S. subprime crisis to emerging markets: Evidence on the decoupling–recoupling hypothesis." Journal of International Money and Finance 28, no. 8: 1331-1349.

Escanciano, J.C., and Olmo, J. (2011) " Robust Backtesting Tests for Value-at-risk Models." *Journal of Financial Econometrics*, 9, No. 1, 132–161.

European Commission, (2009). Economic crisis in Europe: causes, consequences and responses, Office for Official Publications of the European Communities.

Engle, R. F. (1982) "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation." Econometrica 50: 987-1007

Fan, Y., Zhang, Y-J. , Trai, H-T., and Wei, Y-M. (2008) " Estimating 'Value at Risk' of Crude Oil Price and its Spillover Effect Using the GED-GARCH approach." Energy Economics 30: 3156-3171.

Felices, G., and T. Wieladek. 2012. "Are Emerging Market Indicators of Vulnerability to Financial Crises Decoupling from Global Factors?" Journal of Banking and Finance 36, no. 2: 321-331.

Fidrmuc, J., and I. Korhonen. 2010. "The Impact of the Global Financial Crisis on Business Cycles in Asian Emerging Economies." Journal of Asian Economics 21, no. 3: 293-303.

Frank, N., and H. Hesse. 2009. "Financial Spillovers to Emerging Markets during the Global Financial Crisis." Finance a Uver/Czech Journal of Economics and Finance 59, no. 6: 507-521.

Giot, P. and Laurent, S. (2003) "Market risk in commodity markets: a VaR approach." Energy Economics, 25, 435–457.

Giot, P. and Laurent, S. (2004) "Modelling Daily Value-at-Risk Using Realized Volatility and ARCH Type Models." Journal of Empirical Finance, 11: 379-398.

Goodhart, C. A. E. (2008). "The Regulatory Response to the Financial Crisis." Journal of Financial Stability 4(4): 351-358.

Gnamassou, Y.T. (2010) "Value-at-risk prediction: a comparison of alternative techniques applied to a large sample of individual stock data.", MS thesis, HEC Montreal.

Hartz, C. Mittnik, S. & Paolella, M. (2006) " Accurate Value-at-Risk Forecasting Based on the Normal-GARCH Model." *Computational Statistics and Data Analysis* 51: 2295-2312.

Kim, S.; J.-W. Lee; and C.-Y. Park. 2011. "Emerging Asia: Decoupling or Recoupling." World Economy 34, no. 1: 23-53.

Kose, M.A.; C. Otrok; and E.S. Prasad. 2008. "Global Business Cycles: Convergence or Decoupling?" National Bureau of Economic Research Working Paper Series No. 14292

Kupiec, P.H., 1995. "Techniques for verifying the accuracy of risk measurement models." Journal of Derivatives 3, 73–84.

McAleer, M., Veiga, B., and Hoti, S. (2011) "Value-at-Risk for country risk ratings", Mathematics and Computers in Simulation, 81, 1454–1463

Poon, S.-H. & Granger, C. W. J. (2003) "Forecasting Volatility in Financial Markets: A Review." Journal of Economic Literature 41: 478-539.

Orhan, M. and Köksal, B., 2012 "A Comparison of GARCH Models for VaR Estimation", Expert Systems with Applications, 39, 3582-2592, 2012.

Saadi Sedik, T., and O. Williams. 2011. Global and Regional Spillovers to GCC Equity Markets. (International Monetary Fund, IMF Working Papers: 11/138).

So, M.K.P. and Yu, P.L.H., 2006 "Empirical analysis of GARCH models in value at risk estimation", Int. Fin. Markets, Inst. and Money 16 180–197.

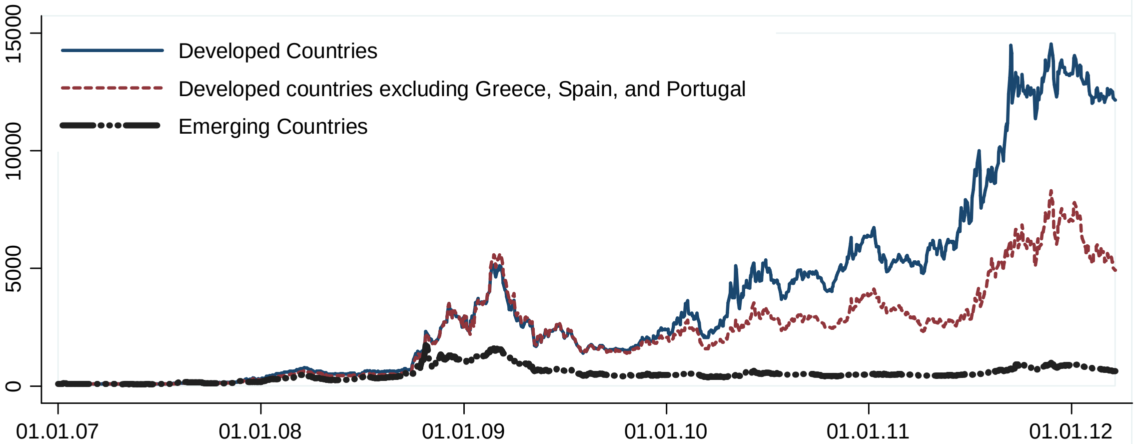
Tang, T-L, Shieh, S-J. (2006) "Long Memory in Stock Index Futures Markets: A Value-At-Risk Approach", Physica A, 306, 437-448.

Tett, G. "Genesis of the debt disaster", Financial Times, May 1, 2009.

Uckun, D., and M. Doerr. 2010. "Emerging Markets: Theory and Practice/Turkey's Reforms Post 2001 Crisis." Journal of Global Analysis 1, no. 1: 51-73.

Wu P. T., Shieh S.J. (2007) "Value-At-Risk Analysis for Long-Term Interest Rate Futures: Fat-Tail and Long Memory in Return Innovations", Journal Of Empirical Finance, 14, 248-259.

Figure 1. Credit Default Spread Indices (01/01/2007=100)



Source. Bloomberg
Note. CDS Index=100 for 01/01/2007 for each country. The rest of the index is calculated based on percentage changes in CDS spreads. Then average index is calculated for developed and developing countries that have data starting from January 2007.
Developed Countries: Austria, Belgium, France, Germany, Greece, Italy, Japan, Portugal, Spain, Sweden.
Emerging Countries: Brazil, Chile, China, Colombia, Czech Rep., Hungary, Indonesia, Israel, S. Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, S. Africa, Thailand, Turkey.

Table 1. Kupiec Test Results, Developed Countries.

Panel A.

Country	VaR	Kupiec Stat.	F/N	Country	VaR	Kupiec Stat.	F/N
Australia	90	2.4	0.116	Italy	90	11.8 **	0.136
	95	12.4 **	0.078		95	15.3 **	0.081
	99	26.5 **	0.032		99	15.8 **	0.026
Austria	90	12.5 **	0.137	Japan	90	1.8	0.114
	95	23.3 **	0.089		95	4.0 *	0.065
	99	12.1 **	0.024		99	1.7	0.015
Belgium	90	7.4 **	0.128	Netherlands	90	1.0	0.110
	95	23.3 **	0.089		95	6.6 *	0.070
	99	12.1 **	0.024		99	7.3 **	0.020
Canada	90	15.5 **	0.142	Norway	90	24.4 **	0.153
	95	27.1 **	0.092		95	29.8 **	0.095
	99	44.6 **	0.039		99	31.3 **	0.034
Denmark	90	3.1	0.118	Portugal	90	0.0	0.101
	95	4.0 *	0.065		95	1.3	0.059
	99	10.4 **	0.023		99	1.7	0.015
Finland	90	0.0	0.100	Singapore	90	0.8	0.109
	95	2.5	0.062		95	0.5	0.055
	99	0.1	0.011		99	4.7 *	0.018
France	90	7.4 **	0.128	Spain	90	9.1 **	0.132
	95	9.7 **	0.074		95	7.3 **	0.071
	99	10.4 **	0.023		99	10.4 **	0.023
Germany	90	0.5	0.107	Sweden	90	10.4 **	0.134
	95	3.5	0.064		95	9.7 **	0.074
	99	5.9 *	0.019		99	8.8 **	0.021
Greece	90	4.8 *	0.123	Switzerland	90	4.8 *	0.123
	95	12.4 **	0.078		95	8.9 **	0.073
	99	13.9 **	0.025		99	19.8 **	0.028
Hongkong	90	4.2 *	0.080	UK	90	5.8	0.125
	95	3.4	0.037		95	12.4 **	0.078
	99	5.3 *	0.003		99	17.7 **	0.027
Ireland	90	6.3 *	0.126	USA	90	0.5	0.107
	95	15.3 **	0.081		95	2.5	0.062
	99	5.9 *	0.019		99	5.9 *	0.019

**, and * denote rejections at the 1%, and 5% levels, respectively. F/N is the proportion of violations. The critical values for 1%, and 5% significance levels of the Chi-Square Distribution with 1 degree of freedom are 6.64, and 3.84, respectively.

Panel B.

	# of rejections		# of non-rejections
VaR	**1% Level**	**5% Level**	
90	8	12	10
95	13	16	6
99	14	19	3
Total	35	47	19

Table 2. Kupiec Test Results, Developing Countries.

Panel A.

Country	VaR	Kupiec Stat.		F/N	Country	VaR	Kupiec Stat.		F/N
Brazil	90	3.5		0.119	Malaysia	90	0.6		0.092
	95	6.6	*	0.070		95	1.0		0.043
	99	5.9	*	0.019		99	0.5		0.012
Chile	90	2.4		0.116	Mexico	90	2.4		0.116
	95	6.6	*	0.070		95	5.2	*	0.068
	99	4.7	*	0.018		99	7.3	**	0.020
China	90	6.4	*	0.075	Morocco	90	0.3		0.095
	95	4.7	*	0.035		95	0.0		0.048
	99	5.3	*	0.003		99	3.5		0.017
Colombia	90	12.5	**	0.066	Peru	90	0.1		0.104
	95	4.7	*	0.035		95	0.5		0.055
	99	2.5		0.016		99	0.1		0.011
Czech Rep	90	0.1		0.097	Philippines	90	0.1		0.102
	95	0.0		0.051		95	0.0		0.050
	99	7.3	**	0.020		99	2.5		0.016
Egypt+	90	NA			Poland	90	4.8	*	0.123
	95	NA				95	5.9	*	0.069
	99	NA				99	8.8	**	0.021
Hungary	90	10.4	**	0.134	Russia	90	9.2	**	0.071
	95	10.5	**	0.075		95	2.8		0.038
	99	15.8	**	0.026		99	0.0		0.010
India	90	1.5		0.113	South Africa	90	0.6		0.108
	95	3.5		0.064		95	4.6	*	0.066
	99	5.9	*	0.019		99	4.7	*	0.018
Indonesia	90	4.2	*	0.080	Taiwan	90	0.0		0.099
	95	0.3		0.046		95	0.0		0.051
	99	0.1		0.009		99	5.3	*	0.003
Israel	90	16.3	**	0.062	Thailand	90	1.0		0.090
	95	3.4		0.037		95	0.5		0.055
	99	3.4		0.005		99	0.4		0.008
Korea	90	0.8		0.091	Turkey	90	0.6		0.092
	95	0.0		0.050		95	0.1		0.047
	99	1.0		0.014		99	0.1		0.009

+ : Insufficient number of convergences for Egypt.

**, and * denote rejections at the 1%, and 5% levels, respectively. F/N is the proportion of violations. The critical values for 1%, and 5% significance levels of the Chi-Square Distribution with 1 degree of freedom are 6.64, and 3.84, respectively.

Panel B.

	# of rejections		# of non-rejections
VaR	**1% Level**	**5% Level**	
90	4	7	14
95	1	8	13
99	4	10	11
Total	9	25	38

Table 3. Christoffersen Test Results

	Developed Countries				Developing Countries			
VaR	**Country**	**Chris.Test**	**Country**	**Chris.Test**	**Country**	**Chris.Test**	**Country**	**Chris.Test**
90	Australia	4.28	Italy	24.86 **	Brazil	9.96 **	Malaysia	6.32 *
95		18.12 **		18.48 **		13.30 **		12.49 **
99		27.68 **		30.15 **		8.20 *		2.90
90	Austria	30.67 **	Japan	2.27	Chile	17.61 **	Mexico	11.84 **
95		44.53 **		5.43		18.04 **		24.04 **
99		12.54		4.24		6.99 *		11.18 **
90	Belgium	25.29	Netherlands	22.41 **	China	13.02 **	Morocco	29.06 **
95		41.70		20.79 **		5.49		19.04 **
99		23.09 **		20.84 **		10.69 **		20.24 **
90	Canada	27.26 **	Norway	33.61 **	Colombia	28.86 **	Peru	14.09 **
95		28.99 **		38.13 **		17.26 **		8.65 *
99		51.09 **		37.04 **		13.87 **		3.08
90	Denmark	23.62 **	Portugal	7.29 *	Czech R.	13.50 **	Philippines	8.59 *
95		18.09 **		1.73		10.39 **		3.16
99		13.54 **		4.24		15.54 **		4.12
90	Finland	11.55 **	Singapore	5.33	Egypt+	NA	Poland	20.04 **
95		7.94 *		2.39		NA		23.88 **
99		3.08		5.82		NA		9.48 **
90	France	17.65 **	Spain	15.08 **	Hungary	28.80 **	Russia	22.71 **
95		14.79 **		11.72 **		24.13 **		17.15 **
99		13.54 **		13.54 **		21.25 **		3.12
90	Germany	8.79 *	Sweden	18.18 **	India	16.64 **	S. Africa	3.19
95		6.43 *		13.15 **		12.63 **		5.85
99		6.90 *		11.01 **		10.22 **		9.41 **
90	Greece	12.85 **	Switzerland	14.45 **	Indonesia	23.35 **	Taiwan	0.23
95		20.06 **		23.82 **		13.27 **		1.31
99		19.83 **		21.59 **		3.74		10.69 **
90	Hong Kong	11.01 **	UK	11.53 **	Israel	16.55 **	Thailand	11.42 **
95		7.86 *		16.43 **		5.47		14.65 **
99		10.69 **		19.76 **		10.01 **		4.62
90	Ireland	14.41 **	USA	0.78	Korea	4.00	Turkey	3.53
95		23.65 **		3.36		5.34		3.91
99		6.90 *		8.20 *		8.00 *		3.42

+ : Insufficient number of convergences for Egypt.

**, and * denote rejections at the 1%, and 5% levels, respectively. The critical values for 1%, and 5% significance levels of the Chi-Square Distribution with 2 degrees of freedom are 9.21, and 5.99, respectively.

Panel B.

	Developed Countries			Developing Countries		
	# of rejections		# of non-rejections	# of rejections		# of non-rejections
VaR	**1% Level**	**5% Level**		**1% Level**	**5% Level**	
90	15	17	5	15	17	4
95	14	17	5	13	14	7
99	14	17	5	11	14	7
Total	43	51	15	39	45	18

Table 4. Average Quadratic Loss

Panel A.

	Developed Countries				Developing Countries			
VaR	**Country**	**AQL**	**Country**	**AQL**	**Country**	**AQL**	**Country**	**AQL**
90	Australia	0.116	Italy	0.136	Brazil	0.119	Malaysia	0.092
95	(12)	0.078	(19)	0.081	(16)	0.070	(6)	0.043
99		0.032		0.026		0.019		0.012
90	Austria	0.137	Japan	0.114	Chile	0.116	Mexico	0.116
95	(20)	0.089	(7)	0.065	(15)	0.070	(15)	0.068
99		0.024		0.015		0.018		0.020
90	Belgium	0.128	Netherland:	0.110	China	0.075	Morocco	0.095
95	(18)	0.089	(8)	0.070	(2)	0.035	(10)	0.048
99		0.024		0.020		0.003		0.017
90	Canada	0.142	Norway	0.153	Colombia	0.066	Peru	0.104
95	(20)	0.092	(21)	0.095	(3)	0.035	(12)	0.055
99		0.039		0.034		0.016		0.011
90	Denmark	0.118	Portugal	0.101	Czech R.	0.097	Philippines	0.102
95	(9)	0.065	(3)	0.059	(11)	0.051	(11)	0.050
99		0.023		0.015		0.020		0.016
90	Finland	0.100	Singapore	0.109	Egypt	NA	Poland	0.123
95	(2)	0.062	(4)	0.055		NA	(17)	0.069
99		0.011		0.018		NA		0.021
90	France	0.128	Spain	0.132	Hungary	0.134	Russia	0.071
95	(11)	0.074	(15)	0.071	(18)	0.075	(4)	0.038
99		0.023		0.023		0.026		0.010
90	Germany	0.107	Sweden	0.134	India	0.113	S. Africa	0.108
95	(6)	0.064	(16)	0.074	(14)	0.064	(13)	0.066
99		0.019		0.021		0.019		0.018
90	Greece	0.123	Switzerlanc	0.123	Indonesia	0.080	Taiwan	0.099
95	(13)	0.078	(10)	0.073	(5)	0.046	(8)	0.051
99		0.025		0.028		0.009		0.003
90	Hong Kong	0.080	UK	0.125	Israel	0.062	Thailand	0.090
95	(1)	0.037	(17)	0.078	(1)	0.037	(8)	0.055
99		0.003		0.027		0.005		0.008
90	Ireland	0.126	USA	0.107	Korea	0.091	Turkey	0.092
95	(14)	0.081	(5)	0.062	(9)	0.050	(7)	0.047
99		0.019		0.019		0.014		0.009

Panel B.

VaR	Developed Countries	Developing Countries
90	0.121	0.097
95	0.072	0.053
99	0.022	0.014