# Empirical investigation of stock return and risk as reflected by conditional volatility, downside risk, and fear

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**Abstract**

This paper tests the risk-return relations by employing risk from conditional volatility, domestic downside risk, world downside risk, and fear. We find a positive and significant intertemporal relation between stock return and risk. The evidence supports the risk-return tradeoff not only from domestic risk but also from external risk. The model is robust with respect to risk with small variations as well as risk feathering from a big shock. The results are robust across 20 different stock markets, different measures of stock returns, and downside risk after controlling the lagged dividend yield.

*JEL classification*: G11, G12, G15

*Keywords*: downside risk; value-at-risk; GARCH-M model; risk-return; market integration

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## 1. Introduction

Following Merton's (1973) seminal article on intertemporal capital asset pricing model (ICAPM) that posits a positive relation between stock return and risk, a substantial amount of empirical studies has been devoted to the investigation of the risk-return relation. In the empirical tests, the Merton's notion is typically specified as a regression model by relating excess stock returns to conditional variance using GARCH-in-M models (Bollerslev, et al., 1992; Bollerslev, 2010).[1] Empirical studies by French, Schwert and Stambaugh (1987), Scruggs (1998), Ghysels et al. (2005), Bali and Peng (2006), and Lundblad (2007) find a positive relation. However, by testing the same hypothesis, Campbell (1987), Nelson (1991), and Glosten, Jagannathan, and Runkle (1993) cannot find sufficient evidence to support this relation, sometimes even finding a negative relation. The main difficulty faced by even the most careful researchers in testing the risk-return relation is the lack of a concise way to measure risk, which is often subject to the rationale of researchers when justifying a measure of risk (Ghysels et al., 2005). There is also a concern regarding whether a Gaussian-type GARCH model is an appropriate procedure to derive the conditional variance for examining the risk-return relation, especially when applying data to an extremely volatile environment.

To address the lack of consensus on the risk-return relation, empirical studies have sought to identify missing variable(s) that could be used to refine proposed models. For instance, some studies (Scott and Horvath, 1980; Fang and Lai, 1997; Harvey and Siddique, 1999; Harvey et al., 2010)

[1] The research along this line has been popularized by the conditional variance using the generalized autoregressive conditional heteroscedasticity in mean (GARCH-M) model and its extensions to exponential GARCH (Nelson, 1991) and threshold GARCH (Glosten et al., 1993). Bollerslev (2010) contains an encyclopedic type reference of ARCH acronyms used in the finance literature.

attempt to incorporate the higher moments into the test equation to highlight the notion that asset pricing should go beyond the traditional approach that mainly relies on mean-variance approach. Pero (1999) and Harvey and Siddique (1999) observe that investors are not only averse to the risk toward conditional variance but also to higher moments. The studies of Fang and Lai (1997), Harvey, Liechty, Liechty and Muller (2010), Chiang and Li (2013) and Lambert and Hübner (2013) find that higher moments are significant factors in explaining stock returns.

Despite the evidence that higher moment based risk factors appear to be consistent with risk aversion behavior, their statistical properties show a strong outlier sensitivity compared with the measure of value-at-risk (VaR) as noted by Cont et al. (2010). By using the Cornish-Fisher expansion (1937), a VaR based on a specific quantile of return distribution links to higher moments of a random variable. In addition, the VaR measure not only specifies the model more parsimoniously but also allows us to address the extreme tail behavior, capturing the price volatile movements, especially during a crisis period (Alexander and Baptista, 2002; Jorion, 2006, Bali et al., 2009; Chen and Chiang, 2016). For these reasons, VaR becomes a commonly chosen risk measure in both academics and the industry (Alexander and Baptista, 2002; Jorion, 2006; Bali, Demirtas and Levy, 2009; Cont, Deguest and Scandolo, 2010).

The literature on international capital asset pricing models highlights the significant effect of risk transmitted from the international market through the volatility spillover (Hamao, Masulis and Ng, 1990; Caporale, et al., 2006; Wongswan, 2006) or contagion effect (Forbes and Rigobon, 2002; Chiang, et al., 2007; Anderson and Vahid, 2007; Forbes, 2012). The episodes of the 1997 Asian crisis and the 2007-2008 world finance crisis attest to the significant spillover of risk. Combining the above two sets of empirical evidence, it is appropriate to ask whether financial assets should be priced locally or globally (Karolyi and Stulz (2003). Further, in their study on the linkage between the US and Japanese markets, Karolyi and Stulz (1996) show that only large shocks to market stock indices positively impact both the magnitude and persistence of return correlations. This finding implies that a rise in downside risk in one market is likely to affect the investment sentiments in another international market, causing a demand for a higher premium for holding stocks. Here the empirical regularity prompts us to ask whether a stock return is better explained by the risk generated from conditional variance that is characterized by smaller and smoother return variations or by downside risk that carries a negative, big price change from domestic or world markets.

The above thought process motivates us to specify a mixed data model that is capable of accommodating a broad coverage of risk content to explain stock returns. Specifically, the risk data generated from a GARCH-type modeling process provide us a measure of risk series smoothly, while the risk data obtained from VaR series offer us risk observations that characterize big changes or jumps. Complementarily each other, both types of risk measures form a wider set of information to explain stock returns. Our empirical analysis suggests that relying on a single measure of risk to predict stock premium is likely to result in a specification error. Unlike previous studies, this paper employs four different measures of risk: conditional standard deviation, local VaR, world VaR, and fear index as measured by the US St. Louis Fed stress index (STLFSI). The conditional standard deviation and local VaR are used to measure local risk, while world VaR and the STLFSI or VIX are used to measure foreign risk. Evidence emerging from this study suggests that all the above-mentioned risks significantly predict (excess) stock returns, supporting the risk-return tradeoff.

This study makes several contributions to the current literature. First, the evidence indicates that a stock return can be positively predicted by downside risk, reflecting the risk aversion of investors who are willing to take a big risk to absorb stocks into their portfolio when faced with dramatic price declines. Second, the downside risk and return relation holds true not only in the local market, but also in the international market regardless of whether global risk is measured by the US's stress index or by the world stock index. Third, besides the downside risk, US market stress risk and world downside risk, the conditional variance/standard deviation has been consistently shown to have a positive sign and to be statistically significant. Fourth, by using a different nonparametric method to measure the downside risk, we obtain a comparable result. In addition, the test results are robust when we replace the stock return with excess stock return. Fifth, beyond the estimations using G7 market data, robustness tests using Latin American and Asian stock return data produce the same qualitative result in our model. Sixth, it is interesting to point out that all market returns are positively related to market fundamentals when a lagged dividend is used as a control variable.

The remainder of the paper is organized as follows. Section 2 presents an analytical framework on the risk-return relation that leads to the formulation of a GED-GARVH-M model for empirical analysis. Section 3 describes the data and different measures of risk. Section 4 presents some empirical estimations using different variables as independent variables. Section 5 conducts robust tests that use different measures of stock returns and downside risk, applying the data to global markets beyond the G7 group. Section 6 contains concluding remarks.

## 2. The analytical framework

### 2.1 *Volatility, downside risk and stock return*

The intertemporal capital asset pricing model (ICAPM) proposed by Merton (1973, 1980) posits that expected excess return is positively related to the market risk. The excess stock return is expressed as a linear function of its conditional variance/standard deviation, and can be expressed as:

$$E_{t-1} r_{it} = \lambda_i E_{t-1}(\sigma_{it}^p) \tag{1}$$

where $E_{t-1}$ is an expectation operator at time $t$-1, $E_{t-1} r_{it}$ is the conditionally expected excess return on market $i$, $E_{t-1}\sigma_{it}^P$ is its conditionally expected variance ($p$=2) or standard deviation ($p$ =1) (see French et al., 1987); $\lambda_i = E_{t-1} r_{it} / E_{t-1}\sigma_{it}^p$ is a measure of relative risk aversion to local market $i$. If the estimated $\lambda_i$ turns out to be positive, then the local investors are risk averse to market $i$, which is consistent with tradeoff hypothesis between risk and return. Yet, in the conventional approach, evidence provided in French, et al (1987) and the survey by Bollerslev, et al (1998) and subsequent studies by Whitelaw (1994), Scruggs (1998), and Bali and Peng (2006) are based on the assumption of the Gaussian distributions. In practice, these studies are unable to highlight the asymmetric risk aversion behavior (Glosten et al., 1993), nor can they effectively capture the investor's reaction to higher moments (Harvey and Siddique, 1999; Chang et al, 2013; Chen et al., 2016). In this context, Scott and Horvath (1980) and Chiang and Li (2013) explicitly address the possibility that investor behavior is averse to variance, kurtosis and negative skewness. Thus, it is appropriate to introduce the Cornish-Fisher expansion (CFE; Cornish and Fisher, 1937), which connects the $\alpha$-quantile of the probability distribution of return, $q_\alpha$ to its corresponding skewness and excess kurtosis as:

$$q_\alpha = [\ z_\alpha + \frac{1}{6}\,(z_\alpha^2 - 1)S + \frac{1}{24}(z_\alpha^3 - 3z_\alpha)k - \frac{1}{36}(2z_\alpha^3 - 5z_\alpha)S^2] \tag{2}$$

where $z_\alpha$ is the $\alpha$-quantile value of a standard normal distribution, $S$ is the standardized skewness, $k$ is the standardized excess kurtosis. Let us define $VaR_{it}$ as the modified VaR of market $i$, which is given by equation (3) below (Zangari, 1996; Agouram and Lakhnati, 2015) as the average return minus the product of $q_{it}$ (at $\alpha$ % level) and $\sigma_{it}$, that is

$$VaR_{it}(\alpha) = \bar{R} - q_\alpha \sigma_{it} \tag{3}$$

where $\sigma_{it}$ is the standard deviation of the stock return distribution for country $i$. Thus, we can write:

$$E_{t-1}r_{it} = \lambda_i^* E_{t-1}(VaR_{it}) \tag{4}$$

where $\lambda_i$ is a measure of relative risk aversion to the downside risk in the local market.[2] In an integrated market, the downside risk from the rest of the world may have a significant impact on the local market due to financial contagion, especially when a big shock occurs (Karolyi and Stulz, 1996; Longin and Solnik, 2001). Following the spirit of Bekaert and Harvey (1995) and Bali and Cakici (2010), equation (4) can be generalized as:

$$E_{t-1}r_{it} = \lambda_i^* E_{t-1}(VaR_{it}) + \lambda_w E_{t-1}(VaR_t^w) \tag{5}$$

where $VaR_t^w$ is the world downside risk, $\lambda_w$ is a measure of relative risk aversion from the world market. A positive value of $\lambda_w$ reflects that investors are risk averse to the risk from world market. A special feature of this model is that unlike the existing specification, which uses the covariance of domestic return and world return to explain risk premium, here we test the correlation of excess return and world downside risk directly. Thus, equation (5) posits that the excess stock return is associated with both the domestic and world downside risks.[3]

## 2.2 . *The GED-GARCH-M model*

In the empirical estimations, Equation (5) can be specified as a GED-GARCH-M model plus the control variable, dividend yield, $DY_{it-1}$, and the expression is given by:

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[2] There are several reasons why we select downside risk in explaining a positive risk-return relation. First, there is extensive literature (Roy, 1952) on top priority that investors place on safety as a way to minimize the probability of big losses. Highly risk-averse behavior under extreme market conditions is more revealing in downside risk. Second, capital adequacy of a firm can be judged on the basis of the amount of this expected loss over a specific time frame (Bali et al., 2009). Third, since VaR emphasizes negative and big breaks in stock returns, it provides insights into the interpretation of the economic sources of model instability (Pettenuzzo and Timmermann, 2011).

[3] Due to possible correlation between $VaR_{it}$ and $VaR_t^w$ as influenced by contagion effect, in the empirical analysis, we will neutralize the local effect.

$$r_{it} = C + \gamma_i \sigma_{it} + \beta_i VaR_{it-1} + \beta_w VaR^{w}_{t-1} + \delta DY_{it-1} + \varepsilon_{it} \quad (6)$$

$$\varepsilon_{it} \,|\, \Omega_{t-1} \sim \text{GED}(0, \sigma^2_{it}, \nu)$$

Equation (6) provides a fundamental equation to test whether excess stock return is correlated with the conditional volatility, the conditional local downside risk and conditional world return downside risk. $\sigma_{it}$ is the conditional standard deviation. This GARCH-M term has been commonly used to test a risk-return relation. The risk aversion hypothesis tests the null: $\gamma_i = 0$, while downside risk aversion hypothesis tests the null $\beta_i = 0$ or $\beta_w = 0$ or both. Because Karolyi and Stulz (1996) note that unexpected changes in macroeconomic variables are not very informative for explaining monthly stock returns, we follow Menzly et al (2004), Pettenuzzo and Timmermann (2011), and Chen and Chiang, 2016) and only include the lagged dividend yield ($DY_{it-1}$) in the test equation as a control variable and proxy for the economic fundamental. Finally, the conditional variance is assumed to evolve with a threshold GARCH (1,1) process (Glosten et al., 1993) and is given by:[4]

$$\sigma^2_{it} = \omega + a\varepsilon^2_{it-1} + b\sigma^2_{it-1} + d\varepsilon^2_{it-1} I^{-}_{t-1}, \quad (7)$$

where $I^{-}_{t-k} = 1$ if $\varepsilon_{t-k} < 0$ and 0, otherwise. Following Nelson (1991) and Li et al (2005), we apply the GED distribution to model stock return innovations. The density function of the GED distribution is expressed as:

$$f(\varepsilon_t) = \nu\{\exp[-(0.5) \,|\, {}^{\varepsilon_t/\sigma_t} /\lambda \,|\, ^{\nu}]\}\{\lambda 2^{(1+1/\nu)}\Gamma(1/\nu)\}^{-1} \quad (8)$$

[4] This model is also known as GJR specification (Glosten et al., 1993). Alternatively, one can use the exponential GARCH model proposed by Nelson (1991). The use of GARCH(1,1) is popularized by Bollerslev et al (1992 ) as a way to achieve a better fit of the stock return equation. Bollerslev (2010) provides a summary of different specification of GARCH-type models.

where $\Gamma(\cdot)$ is the gamma function, and $\lambda$= $\{[2^{\left(-\frac{2}{\nu}\right)}\Gamma(1/\nu)]/\Gamma(3/\nu)\}^{1/2}$. Note that the GED is quite general and is able to model the fat-tail. Moreover, it encompasses different density functions, depending on the value of the parameter $\nu$. When $\nu = 2$, the series becomes a standard normal distribution. When $\nu$ < 2, the distribution has thicker tails than the normal; when > 2, the distribution has thinner tails than the normal (Nelson, 1991). When $\nu \longrightarrow \infty$, we have a uniform distribution.

**3. Data description and estimating downside risk**

The empirical analyses in this study cover the data of the world stock index and world stock excluding the US stock index. These countries/markets include G 7: Canada (CA), France (FR), Germany (BD), Italy (IT), Japan (JP), the United Kingdom (UK), the United States (US). In the robust tests, both Latin America and Asia markets are included. The Latin America markets are: Argentine (AR), Brazil (BR), Chile (CL), Mexico (MX), and Pero (PR); Asia markets are: China (CN), Hong Kong (HK), Indonesia (ID), South Korea (KO), Malaysia (MA), Singapore (SG), Thailand (TH), and Taiwan (TW). All the data are downloaded from a data base of *datastream* for the sample period January 1990 through June 2016. Note that there are some markets such as Latin America and Asia whose interest rate data are available much later. The estimations for some markets' excess stock returns are subjected to the availability of the starting period of the data. The original data are collected on a daily basis, and the monthly data are calculated from the first day of the month through the end of the month. The stock return is measured by taking the natural log-difference of the stock price index times 100. The dependent variable in our regression involves stock return, total stock return (the percentage change in price index plus the dividend yield), and the excess stock return measured as the total stock return minus the one-month Euro-currency rate for the G7 markets, and the one-month bank deposit rate for the Latin and Asian markets. Following Bekaert and Harvey (1995) and Bali and Cakici (2010,) the stock prices are measure using the US dollar.

The downside risk is measured by VaR as proposed by Bali et al. (2009). The estimation is based on the left tail of the actual empirical distribution. The VaR is derived from the minimum daily stock return during the past 21 days as proposed by Bali et al. (2009). For convenience of estimation and interpretation, the VaR used in our regressions is defined as (-1) times the maximum likely loss. Thus, estimating a positive sign for the slopes of the intertemporal term is consistent with risk aversion behavior as reflected in investors' demand for excess compensation for the higher risk. Thus, a positive coefficient for the regression estimate between stock return and a lagged downside risk supports the trade off hypothesis.

In this paper, we also use the bootstrapped data to generate the VaR series. This nonparametric approach is attractive because of its ability to avoid the danger of wrongly specifying the distribution of the risk factor. This is especially true when the distribution is left skewed with non-continuous jumps in returns as experienced during the crisis period that propped a big financial disturbance (Cheung and Powell, 2012).[5] In this study, we generate a sample of 21 bootstrapped daily returns by 1,000 times and obtain a sequence of bootstrapped VaR measures, $\{VaR_{t,s}(\alpha = 1\%): s = 1, \dots, 1{,}000\}$; then we take the sample mean of $VaR_{t,s}(\alpha)$ values to obtain the monthly bootstrapped point estimate $\overline{VaR}_{ts}(\alpha = 1\%)$.[6]

Table 1 reports summary statistics of monthly stock returns for the G7 and world markets. The results for the US perform most distinctly, with the highest values for the mean, median and relative lower standard deviation. The Japanese market, on the other hand, appears to display a negative mean value accompanied by a rather high volatility, resulting in the worst portfolio performance.

[5]Cheung and Powell (2012) provide a step-by-step approach for bootstrapping data.

[6] We will provide more a detailed illustration in section 4.

Table 2 presents the correlations among different markets. As anticipated, the time series plots of G7 in Fig. 1 present a high degree of comovements.

<Tables 1 and 2>

<Fig. 1>

Table 3 reports statistics for different markets using two fundamental variables: the conditional volatility and downside risk. The conditional volatility is generated by a simple GARCH(1,1) process for each market, while a proxy for the downside risk is the value-at-risk $(VaR_t)$, which is calculated as (-1) times the minimum of stock returns observed in the past 21 trading day (see Bali et al., 2009).[7] The statistics in Table 3 suggest that Canada has relative a lower risk in terms of mean values of $\sigma_t^2$ and $VaR_t$; however, the German market has the highest risk in terms of mean values of $\sigma_t^2$ and $VaR_t$ among the G7 markets. As depicted in Fig. 2.A-2.B, the plots of the trajectory of two risk time paths exhibit very similar time series patterns as demonstrated by spikes and dips that occur quite consistently over time. However, the magnitudes for the downside risk series are much larger than that of the variance, indicating that different measures of risk may reflect different informational content even though some common factors are involved. However, as we check the time series plots across markets within each risk, these risk measures produce some degree of comovements, showing some degree of market integration or risk spillover, especially during the higher crisis period.

<Table 3>

<Figs 2A-2G>

[7] We also use 63 trading days (3 months) to calculate $VaR_t$; however, we do not find any significant difference in the measure. To save space, we only focus on a 21-trading day measure.

To provide a preliminary understanding the nature of risk-return relation, we shall start with the conventional approach. This process involves estimating the stock returns on the risk estimators of conditional variance, which is the sum of squared daily returns over the previous month (see French et al. (1987)) using the lagged dividend yield as a control variable. The results reported in Panel A of Table 4 show that the coefficients of volatility at the current period are negative, and lagged values are positive and highly significant. These outcomes are consistent with the market phenomenon in daily trading activity. As investors face a volatile market environment, they tend to reduce their stocks holding, bidding down prices. Thus, we observe a negative correlation between stock return and current volatility. This price reduction is necessary to induce traders to absorb stocks into their portfolio. The subsequent price reversal thus produces profitable trading, leading to a positive relation between the stock return and lagged market volatility.

A similar phenomenon presents in the estimated results by regressing the stock returns on the lagged downside risk defined by Bali et al (2009). The positive and significant sign is consistent with the investors' demand for an even higher risk premium when they encounter an extreme price falls, which triggers a fear for further aggravation of prices. This situation leads to a positive relation between downside risk and return.

## 4. Empirical estimations

### 4.1. *Evidence of risk-return relation in a single market*

To provide a preliminary understanding of the nature of the risk-return relation, we start with the traditional approach of estimating the stock return equation by regressing a stock return on stock return variance ((French et al., 1987), downside risk, and lagged dividend yield (Bali et al., 2009, Chen and Chiang 2016). The results, which are derived by the OLS procedure, are reported in the Table 4. The evidence reported in Panel A of Table 4 shows that coefficients of volatility at the current period are negative, and lagged values are positive and highly significant. These results are consistent with the market phenomenon in daily trading activity. As investors face a volatile market environment, they tend to reduce their stocks holding, bidding down prices. Thus, we observe a negative correlation between stock return and current volatility. This decline in stock prices provides an incentive to risk taking investors who will absorb more moderately priced stocks into their portfolio. Thus, a rise in prices in the subsequent period is a reward for bearing the risk. This phenomenon justifies the coefficient on the lagged value of downside risk to be positive.

A similar phenomenon holds true for the coefficients of the downside risk on the stock return. As shown in Panel B of Table 4, the coefficient of lagged downside risk is positive and highly significant, reflecting the behavior of risk-averse investors who fearing a further aggravation of price, will demand an even higher risk premium when extremely bad news hits the market. Thus, a higher stock return is positively correlated with downside risk. The preliminary estimations in Table 4 suggest that there are positive and significant intertemporal relations between stock returns and risks. However, the LM test based on $T \cdot R^2$ statistics suggests the non-constancy of stock variance.

4.2. *Evidence of VaR and higher moments*

Although both variance and downside risks are priced, the underlying informational content of risk should be identified. As implied in Cornish-Fisher expansion (1937), much of the information on return variabilities is contained in the downside risk as described in equations (2) and (3).

To conduct a formal test, we regress the downside risk on the higher moments of stock returns. The estimate equation can be written as:

$$VaR_{i,t} = b_0 + b_1\sigma_{it}^2 + b_2 S_{it} + b_3\, k_{i,t} + \varepsilon_{i,t} \tag{9}$$

where $VaR_{i,t}$ is the downside risk for market $i$, and the explanatory variables, $\sigma_{it}^2$, $S_{it}$ and $k_{i,t}$ are, respectively, the variance, skewness and kurtosis of stock returns for market *i* derived from the past 21 daily data. Specifically, $\sigma_{it}^2 = \sum_{d=1}^{n} R_{it}^2 + 2\sum_{d=2}^{D_h} R_{id} \cdot R_{id-1}$ is the sum of the squared past 21 daily returns plus twice the sum of the products of adjacent returns (Bali et al., 2009).[8] Skewness is: $S_{it} = \frac{n}{(n-1)(n-2)}\sum_{d=1}^{n}\left(\frac{R_{it-}\bar{R}}{\sigma}\right)^3$ ; Kurtosis is: $k_{i,t} = \frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum_{d=1}^{n}\left(\frac{R_{it-}\bar{R}}{\sigma}\right)^4 - \frac{3(n-1)^2}{(n-1)(n-3)}$. Implied by the Cornish-Fisher expansion, the restrictions in equation (9) are: $b_1 > 0$, $b_2 < 0$, $b_3 > 0$ as $VaR_{it}$s (and $VaR_{it}^{w}$s) are multiplied by -1 in the regressions estimations.

The estimates of equation (9) are reported in Table 5. The statistical results are indeed interesting. Except for the coefficient of kurtosis in Germany, which lacks significance, all coefficients have their anticipated signs and are highly significant. An implication of this finding is that the VaR, as stated in equation (9), possesses relevant information of high moments of stock returns. Moreover, while conducting the variable test by considering the $R_{it}$ as an omitted variable, the F-statistics in Table 5 strongly suggest that null is rejected, and imply the $VaR_{i,t}$ not only reflects information of high moments of stock returns as stated by equation (9) but also correlates with stock return. Thus, the evidence supports the notion that a stock return is correlated with downside risk, which through the Cornish-Fisher expansion, in turn, links to higher moments of stock returns. This evidence is in line with the findings in the literature (Fang and Lai, 1997); Scott and Horvath, 1980; Chiang and Li, 2013), which posits that investor behavior is averse to variance, kurtosis and negative skewness.

<Table 5>

4.3. *Evidence of conditional volatility and VaR*

[8] As noted by Bali et al. (2009), we do not subtract the sample mean from each daily return in calculating the variance since this adjustment is trivial.

The conventional analysis of risk-return behavior recognizes the heteroscedasticity of variance and posits that the stock return can be modeled by time-varying risk (French et al., 1987; Scruggs, 1998; and Bali and Peng, 2006). Despite this empirical regularity provided by the literature, evidence from the LM test based on $T \cdot R^2$ statistics in Table 4 also indicates the existence of an ARCH effect. Thus, in addition to the downside risk, the conditional volatility (standard deviation) is incorporated into the test equation. In preceding with the analysis, we employ GARCH(1,1) specification and assume the stock return innovations following a GED distribution as expressed in equation (9) (Nelson, 1991). This distribution is appealing, since the error series can be smoothly transformed from a normal distribution into a leptokurtotic distribution (fat tails) or even into a platykurtotic distribution (thin tails).[9] As a result, the GED can accommodate the thickness of the tails of a distribution. Estimated results using GED-GARCH (1, 1) are reported in Table 6.

<Table 6>

The estimated results of Table 6 provide several important empirical insights. First, consistent with the fundamental analysis, the coefficient of the lagged dividend is positive and statistically significant, indicating that the dividend yield serving as a fundamental factor effectively signifies predicting direction of stock returns.

Second, the evidence indicates that using GED-GARCH(1,1) to model the stock return series is appropriate. The coefficients on the GARCH(1,1) components are statistically significant, indicating that stock returns for the G7 market display a volatility clustering phenomenon. The results are consistent with the finding documented by Li et al (2005) and Bali and Peng (2006). With respect to the asymmetric effect of bad news on volatility, the evidence shows that the coefficients for all markets are negative and, except for France, are statistically significant.

[9] A kurtosis above 3 indicates “fat tails,” or leptokurtosis, relative to the normal, or Gaussian, distribution. Platykurtosis refers to a distribution that has a negative excess kurtosis with a relatively flatter peak than a normal distribution.

Third, more striking evidence shows that both the coefficients of conditional volatility and downside risk are positive and highly significant, suggesting that both $\hat{\sigma}_{it}$ and $VaR_{it-1}$ are priced in to stock returns. Specifically, $\hat{\sigma}_{it}$ and $VaR_{it-1}$ represent different types of risk: $\hat{\sigma}_{it}$ helps to capture the risk from monthly returns variations with relatively smaller and smoothing deviations, while the $VaR_{it-1}$ highlights the impact of a big and jump negative shock on the stock returns.

4.4. *Evidence from world market*

The above estimations focus on the stock market activity derived from a domestic market and implicitly assumed no risk is transmitted from the global market. Relaxing a single market assumption and recognizing the trend of gradually evolving market integration (Bekaert and Harvey, 1995; 2005) and global contagion (Karolyi and Stulz, 1996; Li e al., 2005; Chiang et al., 2007), we introduce the world downside risk, $VaR_t^w$, into the test equation, where $VaR_t^w$ is derived in the same way as the measure of $VaR_{it}$, but is applied to the world stock index.

The evidence from Table 7 shows that in addition to the coefficients of conditional volatility, $\hat{\sigma}_{it}$, and the local $VaR_{it-1}$, the incremental variable, $VaR_{t-1}^w$, is also positive and the associated t-statistics are significant, conforming with the theoretical expectations of market behavior and supporting a positive risk-return relation. Thus, both local VaR and world $VaR_t^w$ are priced in to the stock return.

<Table 7>

There are a couple of points that merit comment before reaching a conclusion from the above test. First, estimations from Table 7 show that both local $VaR_{it-1}$ and world $VaR_{t-1}^w$ are significant. However, by constructing the series, we see the information of local $VaR_{it}$ is embodied in the $VaR_t^w$. Keeping the contribution of local country stock index from the world stock index may produce a biased estimator. For this reason, we reconstruct the world VaR series by regressing the $VaR_t^w$ on a constant term plus the local $VaR_{it}$ for each market. The resulting residual gives us the neutralized world VaR series, which is labeled as $VaR_{it}^{wxi}$. Thus, $VaR_{it}^{wxi}$ and $VaR_{it}$ are independent of each other.

Second, from the domestic market point of view, a measure of the global influence of VaR using $VaR_t^w$ series makes no distinction between the downside risk from the US or from the world market. Making this distinction is, however, necessary, since the literature consistently reports that the US financial market has a dominant influence on world financial market activities (Masih and Masih, 2001; Rapach, Strauss, and Zhou, 2013). The severe 2007-2008 world finance crisis, which spread from the US market to rest of the global markets, attests to this significant effect. We shall use the US St. Louis Fed stress index to serve as the measure of "fear" from the US financial market.[10] Hakkio and Keeton (2009) observe that this *fear index* can also capture uncertainty arising from asset fundamentals or unexpected shifts in investor behavior.

4.5. *The impact from the US market*

To address the issues outlined above, we rewrite equation (6) as follows:

$$R_{it} = r_{it} = C + \gamma_i \hat{\sigma}_{it} + \beta_i VaR_{it-1} + \beta_w VaR_{it-1}^{wxi} + \beta_{US} Fear_{t-1} + \delta DY_{it-1} + \varepsilon_{it} \quad (10)$$

$$\varepsilon_{it} \,\big|\, \Omega_{t-1} \sim \text{GED}(0, \sigma_{it}^2, \nu)$$

[10] The construction of the St. Louis Fed's Financial Stress Index (STLFSI) is based on weekly information on 18 individual financial variables, including seven interest rates (the effective federal funds rate, the Treasury bill rate, Baa-rated corporate bonds, Merrill Lynch Asset-Backed Master BBB-rated, etc.), six yield spreads (the yield curve, corporate Baa-rated bond minus the 10-year Treasury, TED, etc.), and five other indicators (Chicago Board Options Exchange Market Volatility Index (*VIX*), Merrill Lynch Bond Market Volatility Index (1-month), etc.). Each of these financial variables captures some aspect of financial stress. It is argued that financial stress is the most important factor (the first principal component in principal components analysis) in explaining the co-movement of the 18 weekly financial variables. The advantage of this index is that it provides a measure of composite indexes and avoids the bias resulting from a single indicator. The average value of the index is designed to be zero. The value of zero is viewed as representing normal financial market conditions. Values below zero suggest below-average financial market stress, while values above zero indicate above-average financial market stress.

where $R_{it}$ is a stock return, $VaR_{it}^{wxi}$ is the world downside risk excluding the local $VaR_{it-1}$, and $Fear_t$ is measured by the US fear index based on the St. Louis Fed's Financial Stress Index (STLFSI). C, $\gamma_i$, $\beta_i$, $\beta_w$, $\beta_{US}$ and $\delta$ are constant parameters. This model identifies four different measures of risk: the conditional standard deviation ($\hat{\sigma}_{it}$) generated from the local GARCH (1,1) process, the local downside risk ($VaR_{it}$), the world downside risk ($VaR_{it}^{wxi}$), and the fear index ($Fear_t$) from the US market. Evidence reported in Table 8 shows that all estimated coefficients $\gamma_i$, $\beta_i$, $\beta_w$ and $\beta_{US}$ for different markets are positive and highly significant, indicating that the variables measured by conditional volatility, local downside risk, world downside risk and the fear index from the US market are all priced in the stock returns. A special feature of this test is that the statistics confirm that the US financial market has a significant effect on the world stock returns. This phenomenon can be seen in the estimated coefficients, which range from 0.1596 (JP) to 0.6588 (Canada) and are highly significant.

To visualize the time series properties of various risk series, in Figures 3.A-3G, we plot their time paths. Apparently, both $\hat{\sigma}_{it}$ and $Fear_t$ display rather smooth variations relative to the two downside risks and capture smaller fluctuations of changes over time, whereas $VaR_{it}$ and $VaR_{it}^{wxi}$ display more abrupt changes, reflecting much bigger price changes or jump processes. Moreover, $VaR_{it}^{wxi}$ and $Fear_t$ denote risk factors from the world markets. Thus, different elements of risk in equation (10) have their own unique informational content and can be complementarily used to explain stock returns.

<Table 8>

## 5. Robustness checks

5.1. Measuring downside risk by bootstrapped data

It is generally recognized that empirical estimations are often subject to the use of variable, estimated methods and special features of market condition. Robustness tests help us to clarify the validity of the behavioral relations under different settings. One of the concerned issues here is the measure of the downside risk, which is based on the minimum daily market returns in the previous month (Bali et al., 2009). This approach may generate a biased measure of downside risk as evidenced by VaR series that sometimes can only capture the risk quantile at 4-5 level of downside risk Chen et al. (2016).[11] As a result, we shall replace the downside risk measure with bootstrapped data. The bootstrap procedure used in this study involves re-sampling from the existing data with replacements. From this process, we can produce a large number of new samples. Each resampling with a replacement from the past *n* (21) trading days generates a VaR estimate. This procedure is repeated 1,000 times, creating a sequence of bootstrapped VaR series. We then use the sample mean of 1,000 bootstrapped VaRs as the point estimator for the month *t*. Given that the purpose of VaR is to capture behavior in the distribution tails, the bootstrap is ideally suitable to be used with VaR measure (Jorion, 2006). [12]

The estimated equations, which use the bootstrapped data to measure local and world downside risks, are presented in Table 9. All the estimated statistics produce very comparable qualitative results. However, the coefficients of downside risks are smaller when employing bootstrapped data in measuring downside risks. In particular, by comparing the results of Table 9 with that of Table 8, evidence shows that the coefficients of $VaR_{it-1}$ move from the range of 4.2670 (FR) ~5.9389 (CA) to 1.4415 (JP) ~2.2583 (IT), and the $VaR_{it}^{wxi}$ also declines from the range of 0.7337 (CA) ~ 4.4638 (JP) to 0.3149 (CA) ~ 1.9055 (US), reflecting sensitive changes of risk aversion behavior.

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[11] Chen et al. (2016) argue that using Bali et al (2009) approach to derive VaR series sometimes can only capture the risk quantile at 4-5% level of downside risk.

[12] The procedure to generate the VaR series using the bootstrapping method shown in the Appendix.

<Table 9>

## *5.2. Measuring the US market fear by VIX*

In conducting the empirical analysis of stock returns, some researchers prefer to use the expected S&P 100 index option volatility by the Chicago Board Options Exchange (CBOE) as a proxy for fear of the US market (Guo and Whitelaw, 2006; Bali and Engle, 2010; Rapach, Strauss and Zhou, 2013). Whaley (2009) observes that the *VIX* spikes during periods of market turmoil, reflecting changing market conditions wherein expected *VIX* increases (decreases) lead to declines (rises) in stock prices, which prompt investors to require a higher (lower) rate of return to compensate for fluctuating levels of risk. Hakkio and Keeton (2009) further argue that the *VIX* can capture uncertainty arising from asset fundamentals or unexpected shifts in investor behavior. The estimated results of replacing the St. Louis Fed Financial Stress Index by *VIX* are reported in Table 10.

<Table 10>

The evidence shows that the model constantly performs well, which is brought out by the fact that all four risk factors are positive and statistically significant, and the adjusted R-squares produce very comparable explanatory power. However, estimated coefficients of the *VIX* change compared with that of SLFSI. The slope of the coefficients change from 2.6523 to 0.088 for Canada, from 0.6296 to 0.2792 for France, from 1.5947 to 0.3089 for Germany, from 1.0032 to 0.2041 for Italy, from 1.3077 to 0.2097 for Japan, from 1.0074 to 0.3033 for the UK, and from 1.4488 to 0.2512 for the US. Interestedly, a general lower level of coefficients is accompanied by a higher level of t-statistics (except CA) when *VIX* is used as a measure of fear index. It appears that the statistics based on *VIX* produce more consistent effects on stock returns.

## *5.3. Excess stock return as dependent variable*

The parametric tests of the risk-return relations are sensitive to different ways of defining stock returns. For example, defining the stock return as the log-difference of market price index, which was done in the previous estimations, provides us a simple and convenient approach to estimate the risk-return relation. However, to be consistent with the essence of theory and empirical literature, we take a different approach in this section and examine excess stock returns in relation to various forms of risk. Following convention, the excess return is measured by the total market stock return minus one-month Euro-currency for each country ($r_t$ = $R_t$ $-r_{f,t-1}$). The estimated results are reported in Table 11. For all measures of risk, $\hat{\sigma}_{it}$, $VaR_{t-1}$, $VaR_{t-1}^{wxi}$ and $Fear_{t-1}$, slopes are constantly positive and highly significant, supporting a multidimensional tradeoff of risk-return relations. These findings should not be surprising, since each risk measure has its unique informational content of the risk. As we mentioned earlier, the $\hat{\sigma}_{it}$ is the conditional volatility derived from the monthly data of lagged stock return shocks or variance projected by the asymmetric GARCH(1,1) process. It therefore represents a series with regular and smaller return variability; the $VaR_{t-1}$is derived from bootstrapped data based on lagged daily return observations and capture a big and abrupt month return shock. Thus, both types of risk form mixed data frequency and constitute different degrees of return variability from local market risks. A similar feature is revealed in $VaR_{t-1}^{wxi}$ and $Fear_{t-1}$, where the $VaR_{t-1}^{wxi}$ is characterized by an abrupt shock that we bootstrap using daily data for the previous month for the world market, while $Fear_{t-1}$ is the US monthly *VIX* data and appears to be smoother compared with the world $VaR_{t-1}^{wxi}$. Again, these two variables feature mixed data frequency of world risks. By comparing the overall estimated statistics of Table 11 with those of Table 10, there are no significant differences in the estimated parameters of risk-return relations, regardless of whether the stock returns or the excess stock returns are used as the dependent variable. Thus, we confirm that the tests are robust and verify a positive significant relation between stock returns and risk, which allows us to conclude that any model using a single risk factor, such as local market conditional variance or local downside risk to predict the stock risk premium, will likely produce a biased estimator.

<Table 11>

*5.4. Evidence from Latin American and Asian markets*

The positive relation between expected returns and various forms of risk for the G7 markets may well be due the fact they share common information and competitive market condition, and have comparable macroeconomic climate. These market settings and operating system likely motivate the risk averse investors to act in a similar fashion. Therefore, in this section we examine whether the estimated risk averse behavior holds true for other stock markets. The tests include the Latin American market: Argentine (AR), Brazil (BR), Chili (CL), Mexico (MX) and Pero (PR)) and Asian markets: China (CN), Hong Kong (HK), South Korea (KO), Malaysia (MA), Singapore (SG), Thailand (TH) and Taiwan (TW). Results of the model estimates are reported in Table 12 for the five Latin American markets and in Table 13 for the eight Asian markets.[13]

< Tables 12 and 13>

For all market indices, there is a positive and highly significant relation between excess market return and risk measures. As shown in Table 12, after controlling for the lagged dividend yield, t-statistics for Latin American markets range from 1.98 to 6.26 for $\hat{\sigma}_{it}$, from 14.27 to 33.84 for $VaR_{it-1}$, from 2.21 to 6.68 for $VaR^{wx1}_{it-1}$, and from 3.07 to 8.33 for $Fear_{t-1}$ stemming from the US market. T-statistics for Asian markets in Table 13, which parallel those for the Latin American

[13] Due to the fact we could not find statistical significance on the asymmetric term in the variance equation for most markets in the Asian market when making the empirical estimations, the $\varepsilon^2_{it-1}I^-_{t-1}$ term is dropped from the model and a GARCH(1,1) model is maintained.

markets, range from 1.72 to 3.00 for $\hat{\sigma}_{it}$, from 11.49 to 73.40 for $VaR_{it-1}$, from1.64 to 17.27 for $VaR^{wx1}_{it-1}$, and from 2.44 to 15.39 for $Fear_{t-1}$ stemming from the US market. Clearly, the significant t-statistics consistently reject the null that posits excess stock returns are independent of risk factors. However, when we compare the estimated coefficients of the $VaR_{t-1}$, we find they are slightly higher than those for other markets, suggesting that investors in Asian markets are more sensitive to the downside risk. Further, since we are unable to find the asymmetric term in the variance equation to be significant, the asymmetric behavior for the volatility due to bad news is not as obvious in the Asian markets.

## 6. Conclusions

This paper examines the intertemporal relation between risk and expected stock return. We use four different measures of risk: conditional volatility (standard deviation), local downside risk, world downside risk, and the US fear index. The evidence confirms a positive and significant relation, supporting the risk-return tradeoff and risk aversion hypothesis. Testing the data from 20 stock indices in global market and using different definitions to measure stock risk, we obtain several empirical findings. First, the evidence indicates that the stock return is positively correlated with conditional volatility, which is consistent with most conventional model specification (French et al, 1987; Scruggs 1998; Bali and Peng, 2006). Second, we also find supporting evidence for a positive relation between VaR and excess stock returns. This finding holds not only for local markets but also the world market (Bali et al., 2009). Thus, both the local VaR and world VaR are priced in the stock returns, a finding that is in line with the literature (Bali and Cakici, 2010). Third, the evidence reveals that the US fear index possesses significant information to influence each country's stock return. The risk from US market uncertainty responds to risk averse investors, who undoubtedly price fear into stock returns (Chen and Chiang, 2016). Fourth, our empirical evidence suggests that the traditional test to examine the risk-return relation by focusing a single form of risk measure is likely to lead a specification error, since conditional volatility, local downside risk, world downside risk and the US fear index all exhibit a positive and significant relation with the (excess) stock returns. Due to the inclusiveness of risk specification, our model demonstrates robustness in modeling the risk-return relation during relative tranquil periods with small variations revealed in conditional volatility and during the crisis period characterized by big shocks captured by downside risk either from local markets or the world market.

**Appendix:** Procedures to generate VaR series using the bootstrap method

The procedure to generate bootstrapped data is as follows (see Chen and Chiang, 2016):

Step 1: In the beginning of month $t$, generate a sample of $n$ bootstrapped daily returns $\{R_{t-i}: i = 1, \dots, n\}$ by resampling with replacements from the past $n$ trading days;

Step 2: Compute the monthly estimates of VaR, say, $\alpha$% of the quantile, on the bootstrapped daily sample $R_{t-i}$

$$VaR_t(\alpha) = q_\alpha(R_{t-i}), \qquad i = 1, \dots, n$$

where $q_\alpha(\cdot)$ is the $\alpha$ quantile (1%) of the empirical distribution from the bootstrapped sample $R_{t-i}$;

Step 3: By repeating steps 1 and 2 many times (1000 times), we obtain a sequence of bootstrapped risk measures, $\{VaR_{t,s}(\alpha): s = 1, \dots, 1000\}$;

Step 4: By taking the sample mean of $VaR_{t,s}(\alpha)$ values, we obtain the bootstrapped point estimate$\overline{VaR}_{ts}(\alpha)$.

In this study, we set $\alpha = 1\%$ and $n$ =21 days. Here we obtain 310 monthly and non-overlapping estimates of $\overline{VaR}_t(\alpha)$ which avoids the statistical problem of overlapping data (Lettau and Ludvigson, 2010, p. 638). Since the monthly $\overline{VaR}_t(\alpha)$ values are originally obtained from the left tail, the downside risk measure of $\overline{VaR}_t(\alpha)$ is the $VaR_{it}$ multiplied by (-1) before applying it to the empirical estimation (see Bali et al., 2009).

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Table 1. Summary statistics of stock returns for G7 and world markets

The markets under investigation are Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK) and the United States (US) and the world (WD) markets.

| | *Rm_CA* | *Rm_FR* | *Rm_GM* | *Rm_IT* | *Rm_JP* | *Rm_UK* | *Rm_US* | *Rm_WLD* |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.5473 | 0.2998 | 0.5462 | 0.1143 | -0.1854 | 0.3738 | 0.5728 | 0.3935 |
| Median | 0.6187 | 0.9018 | 0.9533 | 0.0440 | 0.2359 | 0.6588 | 1.0049 | 0.7776 |
| Maximum | 13.8870 | 12.5882 | 19.3738 | 21.0905 | 18.2873 | 9.8897 | 10.5790 | 10.3504 |
| Minimum | -25.533 | -19.225 | -29.333 | -16.801 | -27.216 | -13.955 | -18.564 | -21.128 |
| Std. Dev. | 5.5582 | 5.3002 | 6.0168 | 6.0000 | 6.0244 | 3.9511 | 4.0758 | 4.2309 |
| Skewness | -0.6197 | -0.5030 | -0.9437 | 0.1547 | -0.4873 | -0.6222 | -0.8372 | -0.9439 |
| Kurtosis | 4.7714 | 3.5850 | 6.2175 | 3.7985 | 4.4037 | 3.9345 | 5.1717 | 5.5608 |
| Jarque-Bera | 60.3749 | 17.4902 | 179.727 | 9.4721 | 37.7199 | 31.2820 | 97.1264 | 130.7409 |
| Observations | 310 | 310 | 310 | 310 | 310 | 310 | 310 | 310 |

Table 2. Correlations of stock returns for G7 and world markets

This table reports the correlation coefficient of G7 and world markets. The first row is the coefficient and the second row is the corresponding t-statistic. The markets under investigation are Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK), the United States (US) and the world (WD) markets.

| Correlation<br>t-Statistic | *Rm_CA* | *Rm_FR* | *Rm_GM* | *Rm_IT* | *Rm_JP* | *Rm_UK* | *Rm_US* | *Rm_WD* |
|---|---|---|---|---|---|---|---|---|
| *Rm_CA* | 1 | | | | | | | |
| | ----- | | | | | | | |
| *Rm_FR* | 0.65 | 1 | | | | | | |
| | 14.95 | ----- | | | | | | |
| *Rm_GM* | 0.64 | 0.87 | 1 | | | | | |
| | 14.69 | 31.05 | ----- | | | | | |
| *Rm_IT* | 0.56 | 0.76 | 0.72 | 1 | | | | |
| | 11.75 | 20.69 | 18.26 | ----- | | | | |
| *Rm_JP* | 0.43 | 0.50 | 0.48 | 0.48 | 1 | | | |
| | 8.44 | 10.25 | 9.71 | 9.56 | ----- | | | |
| *Rm_UK* | 0.62 | 0.81 | 0.75 | 0.65 | 0.47 | 1 | | |
| | 13.99 | 24.56 | 20.16 | 14.84 | 9.27 | ----- | | |
| *RmUS* | 0.68 | 0.74 | 0.74 | 0.57 | 0.51 | 0.79 | 1 | |
| | 16.30 | 19.27 | 19.20 | 12.25 | 10.38 | 22.78 | ----- | |
| *Rm WD* | 0.62 | 0.78 | 0.76 | 0.65 | 0.68 | 0.81 | 0.92 | 1 |
| | 14.03 | 22.21 | 20.61 | 14.89 | 16.34 | 24.34 | 39.98 | ----- |

Table 3. Summary statistics of volatility and VaR for G7 and world markets

This table presents summary statistics of variance and downside risk. $\sigma_t^2$ and $VaR$ are variance and downside risk, respectively. The $\sigma_{it}^2$ is based on the sum of the squared 21 days daily returns plus twice the sum of the products of adjacent returns. (French et al., 1987); $VaR_{it}$ is derived from the minimum value of daily stock returns in the past 21 days as proposed by (Bali et sl., 2009). The original $VaR_{it}$s are multiplied by -1 before conducting the statistical analysis. The markets under investigation are Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK), the United States (US) and the world (WD) market.

| *Panel A* | $\sigma_t^2$_CA | $\sigma_t^2$_FR | $\sigma_t^2$_GM | $\sigma_t^2$_IT | $\sigma_t^2$_JP | $\sigma_t^2$_UK | $\sigma_t^2$_US | $\sigma_t^2$_WD |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.1863 | 0.3660 | 0.3814 | 0.3486 | 0.3358 | 0.2025 | 0.2366 | 0.1467 |
| Median | 0.0956 | 0.2377 | 0.2281 | 0.2246 | 0.2173 | 0.1144 | 0.1313 | 0.0876 |
| Maximum | 4.8398 | 5.2599 | 4.7693 | 4.4176 | 6.7424 | 4.0874 | 5.0070 | 3.5018 |
| Minimum | 0.0130 | 0.0399 | 0.0146 | 0.0179 | 0.0218 | 0.0130 | 0.0166 | 0.0123 |
| Std. Dev. | 0.3702 | 0.4632 | 0.4925 | 0.4115 | 0.4766 | 0.3235 | 0.4156 | 0.2590 |
| Skewness | 8.1756 | 5.2437 | 4.1125 | 4.5947 | 8.6817 | 6.9255 | 7.0752 | 8.4529 |
| Kurtosis | 91.1538 | 45.4933 | 27.5837 | 36.3766 | 109.079 | 72.855 | 69.4939 | 98.9007 |
| Jarque-Bera | 103830 | 24744 | 8680 | 15480 | 149243 | 65509 | 59697 | 122486 |
| Observation | 310 | 310 | 310 | 310 | 310 | 310 | 310 | 310 |

| *Panel B* | $VaR_t$_CA | $VaR_t$_FR | $VaR_t$_GM | $VaR_t$_IT | $VaR_t$_JP | $VaR_t$_UK | $VaR_t$_US | $VaR_t$_WD |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.7540 | 1.0753 | 1.0936 | 1.0748 | 1.0562 | 0.7708 | 0.8379 | 0.6669 |
| Median | 0.6047 | 0.9694 | 0.9937 | 0.9382 | 0.9109 | 0.6606 | 0.7254 | 0.5773 |
| Maximum | 4.1003 | 4.1134 | 4.2868 | 4.8964 | 4.3458 | 3.7826 | 4.1082 | 2.8894 |
| Minimum | 0.0812 | 0.2160 | 0.1516 | 0.1797 | 0.2412 | 0.1464 | 0.1229 | 0.1018 |
| Std. Dev. | 0.5591 | 0.5876 | 0.6429 | 0.6079 | 0.6062 | 0.4785 | 0.5504 | 0.4323 |
| Skewness | 2.6478 | 1.6617 | 1.6416 | 1.8826 | 1.8943 | 1.8692 | 2.4461 | 2.0884 |
| Kurtosis | 12.9540 | 7.2045 | 6.8320 | 9.3959 | 8.6436 | 8.8314 | 12.2839 | 9.0349 |
| Jarque-Bera | 1642 | 371 | 329 | 712 | 597 | 620 | 1422 | 696 |
| Observation | 310 | 310 | 310 | 310 | 310 | 310 | 310 | 310 |

Table 4. Estimates of stock returns using downside risk and divided yield

The dependent variable is stock return, $R_{it}$. The $\sigma_{it}^2$ is realized variance, which is based on the sum of the squared 21 days daily returns plus twice the sum of the products of adjacent returns. (French et al., 1987). The $VaR_{it}$ is monthly value-at-risk, which is defined as the minimum daily return observed during the past 21 days (Bali et al., 2009). The original $VaR_{it}$s are multiplied by -1 before running regressions. $DY_t$ is the divided yield. Regression results are estimated by OLS method. The estimated values in the first row are the estimated coefficients, the values in second row below coefficients are the t-statistics. Significant levels at the 1%, 5%, and 10% level are 2.60, 1.97, and 1.65, respectively. $T \cdot R^2$ is the LM statistic for testing ARCH(1).The markets are: Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK) and the United States (US).

| Panel A. | $C$ | $\sigma_{it}^2$ | $\sigma_{it-1}^2$ | $DY_{t-1}$ | $T \cdot R^2$ | $\bar{R}^2$ |
|---|---|---|---|---|---|---|
| CA | 1.3305 | -6.6349 | 2.3041 | 0.0187 | 6.23 | 0.12 |
| | 1.05 | -6.08 | 2.09 | 0.04 | | |
| FR | 0.2583 | -6.0460 | 3.1697 | 0.3566 | 19.36 | 0.17 |
| | 0.23 | -8.16 | 4.15 | 0.98 | | |
| GM | 0.8052 | -6.7173 | 3.8719 | 0.3869 | 22.78 | 0.19 |
| | 0.75 | -8.74 | 4.93 | 0.83 | | |
| IT | 1.4651 | -6.1110 | 3.4551 | -0.1151 | 14.28 | 0.14 |
| | 1.75 | -7.05 | 3.80 | -0.45 | | |
| JP | -0.4945 | -4.4275 | 1.5332 | 1.0846 | 11.91 | 0.10 |
| | -0.65 | -6.04 | 2.06 | 1.89 | | |
| UK | -1.9359 | -6.4993 | 3.2765 | 0.8538 | 13.07 | 0.20 |
| | -1.91 | -8.41 | 4.14 | 2.95 | | |
| US | -0.0985 | -5.1739 | 2.0992 | 0.7142 | 29.66 | 0.17 |
| | -0.12 | -7.37 | 2.99 | 1.88 | | |

| Panel B. | $C$ | $VaR_{it-1}$ | $DY_{t-1}$ | $T \cdot R^2$ | $\bar{R}^2$ |
|---|---|---|---|---|---|
| CA | 4.6624 | 4.3448 | -0.3353 | 26.46 | 0.19 |
| | 1.97 | 6.15 | -0.37 | | |
| FR | 2.5908 | 4.2066 | 0.7088 | 9.28 | 0.21 |
| | 2.27 | 9.10 | 2.07 | | |
| GM | 3.6649 | 4.5190 | 0.8093 | 14.65 | 0.23 |
| | 3.32 | 9.69 | 1.84 | | |
| IT | 4.3287 | 4.5460 | 0.2221 | 8.83 | 0.20 |
| | 4.88 | 8.89 | 0.94 | | |
| JP | 2.7021 | 4.1650 | 1.2632 | 10.80 | 0.18 |
| | 3.17 | 8.19 | 2.36 | | |
| UK | 0.4176 | 4.1006 | 0.8950 | 7.56 | 0.26 |
| | 0.42 | 10.22 | 3.33 | | |
| US | 2.9740 | 3.6134 | 0.3243 | 27.30 | 0.24 |
| | 3.49 | 9.78 | 0.88 | | |

Table 5. Regression estimation of $VaR_t$ on Volatility, Skewness and Kurtosis

This table presents estimated results by regression VaR on the higher moments of stock returns.

$$VaR_{i,t} = b_0 + b_1\sigma_{it}^2 + b_2 S_{it} + b_3\, k_{i,t} + \varepsilon_{i,t}.$$

The dependent variable $VaR_{i,t}$ is the downside risk for country *i* and world stock indices are defined as the minimum daily index return observed during the past 21 days (Bali et al., 2009). The original $VaR_{it}$s are multiplied by -1 before running regressions. The explanatory variables, $\sigma_{it}^2,\ S_{it}, and\ k_{i,t}$ are, respectively, the variance, skewness and kurtosis of stock returns for market *i* derived from the past 21 daily stock returns. The original $VaR_{it}$s are multiplied by -1 before running regressions. *F* (1,311) is F-statistic for testing the null, i.e., coefficients on the omitted variable, stock return, is zero. The estimated value in the first row is the estimated coefficient, the second row of the corresponding coefficients gives the t-statistics. The markets under investigation are Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK), the United States (US) and the world (WD) market.

| | C | $\sigma_{it}^2$ | $S_{it}$ | $k_{it}$ | *F* (1,311) | $\bar{R}^2$ |
|---|---|---|---|---|---|---|
| CA | 0.4694 | 1.1968 | -0.2790 | 0.0323 | 39.15 | 0.74 |
| | 11.18 | 4.80 | -7.07 | 2.02 | | |
| FR | 0.6643 | 1.0438 | -0.3095 | 0.0763 | 79.49 | 0.80 |
| | 33.99 | 31.72 | -11.69 | 7.13 | | |
| GM | 1.8391 | 3.8083 | -0.5496 | 0.0623 | 87,47 | 0.76 |
| | 23.65 | 31.27 | -5.32 | 1.49 | | |
| IT | 0.6034 | 1.2152 | -0.2975 | 0.0721 | 22.49 | 0.81 |
| | 29.60 | 32.77 | -11.62 | 6.89 | | |
| JP | 0.7167 | 0.9196 | -0.3658 | 0.0832 | 69.94 | 0.74 |
| | 10.40 | 4.14 | -12.32 | 5.54 | | |
| UK | 0.4989 | 1.2420 | -0.2395 | 0.0636 | 79.01 | 0.78 |
| | 11.42 | 5.50 | -13.37 | 6.60 | | |
| US | 0.5551 | 1.0792 | -0.2766 | 0.0331 | 47.17 | 0.76 |
| | 12.91 | 5.95 | -9.76 | 3.03 | | |
| World | 0.4363 | 1.2793 | -0.2233 | 0.0589 | 61.54 | 0.70 |
| | 10.90 | 4.47 | -8.90 | 4.98 | | |

Table 6. Estimates of stock returns on conditional volatility and domestic downside risk

The dependent variable is total stock return $R_{it}$; the independent variable $\widehat{\sigma}_{it}$ is the conditional volatility measured by the conditional standard deviation from the Threshold GED-GARCH (1,1)-M model. $VaR_{it}$ is the downside risk, which is derived from the minimum of daily stock return in the past 21 days as proposed by Bali et al. (2009). $DY_t$ is the aggregate dividend yield, which serves as a control variable at time *t*. The $\delta, \varepsilon_{it}^2$ and $\sigma_{it}^2$ are, respectively, constant term, shock squared, and conditional variance for market *i* using a threshold GED-GARCH (1,1)-M model. The original $VaR_{it}s$ are multiplied by -1 before running regressions. The values in the first row are the estimated coefficients; the values in the second row are the t-statistics. The significant levels at the 1%, 5%, and 10% level are 2.60, 1.97, and 1.65, respectively. $\bar{R}^2$ is the adjusted *R*-squared. The markets are Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK) and the United States (US).

| | $C$ | $\widehat{\sigma}_{it}$ | $VaR_{it-1}$ | $DY_{t-1}$ | $\delta$ | $\varepsilon_{it-1}^2$ | $\varepsilon_{it-1}^2 I_{t-1}^-$ | $\sigma_{it-1}^2$ | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|---|---|
| CA | -0.3223 | 0.2440 | 3.8420 | 1.0245 | -0.0472 | 0.1993 | -0.1125 | 0.8671 | 0.19 |
| | -0.24 | 2.52 | 10.61 | 2.33 | -1.54 | 3.36 | -1.97 | 25.87 | |
| FR | 0.6343 | 0.4461 | 3.8318 | 0.5492 | 1.3855 | 0.4997 | -0.0240 | 0.7350 | 0.20 |
| | 0.99 | 4.46 | 35.78 | 6.99 | 1.65 | 3.23 | -0.22 | 22.65 | |
| GM | -13.444 | 0.4600 | 4.3818 | 0.2467 | 1.9191 | 0.4552 | -1.3704 | 0.8650 | 0.16 |
| | -4.49 | 14.55 | 8.26 | 5.46 | 3.27 | 5.98 | -6.40 | 2.43 | |
| IT | -4.5139 | 0.6872 | 4.4565 | 0.4533 | 15.1591 | 0.2810 | -0.1703 | 0.8556 | 0.22 |
| | -1.26 | 2.60 | 35.01 | 8.47 | 2.38 | 3.60 | -2.91 | 44.17 | |
| JP | -11.479 | 0.7969 | 3.5297 | 0.7768 | 6.7578 | 0.0078 | -0.7269 | 0.7724 | 0.11 |
| | -2.76 | 3.92 | 47.61 | 4.90 | 3.64 | 0.19 | -3.10 | 35.37 | |
| UK | -10.6746 | 0.8413 | 4.4143 | 0.6028 | 25.4947 | 0.2572 | -0.0946 | 0.8660 | 0.26 |
| | -16.16 | 18.30 | 39.70 | 12.69 | 22.75 | 9.11 | -2.56 | 3.39 | |
| US | -14.7169 | 2.9514 | 5.6676 | 0.6708 | 18.5661 | 0.2066 | -0.2093 | 0.4550 | 0.19 |
| | -10.37 | 6.19 | 65.73 | 9.79 | 3.81 | 3.55 | -3.47 | 11.89 | |

Table 7. Estimates of stock returns on conditional volatility, domestic and world downside risks

The dependent variable is monthly stock return $R_{it}$; the independent variable $\widehat{\sigma}_{it}$ is the conditional volatility measured by the conditional standard deviation from the Threshold GED-GARCH (1,1)-M model. $VaR_{it}$ and $VaR^{w}_{t-1}$ are the local and world market downside risks defined as the minimum of daily stock return in the past 21 days as proposed by Bali et al. (2009). $DY_t$ is the aggregate dividend yield, which serves as a control variable at time *t*. The $\delta, \varepsilon^2_{it}$ and $h_{it}$ are constant, shock squared, and conditional variance for market *i* using a threshold GED-GARCH (1,1)-M model. The original $VaR_{it}$s and $VaR^{w}_{it}$s are multiplied by -1 before running regressions. The values in the first row are the estimated coefficients; the values in the second row are the t-statistics. The significant levels at the 1%, 5%, and 10% level are 2.60, 1.97, and 1.65, respectively. $\bar{R}^2$ is the adjusted *R*-squared. The markets are Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK) and the United States (US).

| | $C$ | $\widehat{\sigma}_{it}$ | $VaR_{it-1}$ | $VaR^{w}_{it-1}$ | $DY_{t-1}$ | $\delta$ | $\varepsilon^2_{it-1}$ | $\varepsilon^2_{it-1}I^-_{t-1}$ | $\sigma^2_{it-1}$ | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| CA | -2.0305 | 0.2849 | 4.0386 | 0.1166 | 0.5238 | 11.8886 | 0.9639 | -0.2550 | 0.8834 | 0.20 |
| | -2.50 | 4.12 | 63.25 | 4.87 | 6.23 | 2.42 | 2.53 | -2.22 | 4.42 | |
| FR | 1.7104 | 0.4379 | 2.7486 | 2.0976 | 0.3179 | 1.1641 | 0.6402 | -0.1472 | 0.7213 | 0.19 |
| | 3.42 | 4.97 | 11.54 | 6.81 | 2.76 | 1.40 | 3.00 | -1.12 | 23.28 | |
| GM | 2.0593 | 0.3418 | 3.8762 | 1.9554 | 1.0141 | 1.3074 | 0.3297 | -0.0397 | 0.7268 | 0.26 |
| | 2.20 | 2.77 | 8.85 | 3.04 | 3.20 | 1.50 | 1.98 | -0.22 | 7.43 | |
| IT | 2.1328 | 0.1267 | 3.8317 | 3.4536 | 0.7349 | 0.1307 | 0.5397 | -0.1049 | 0.8461 | 0.20 |
| | 7.76 | 4.44 | 27.73 | 27.11 | 8.83 | 0.95 | 1.67 | -0.27 | 17.34 | |
| JP | -10.3628 | 0.8576 | 2.1513 | 4.3654 | 1.8038 | 44.5833 | 0.0644 | -0.3869 | 0.7790 | 0.19 |
| | -3.78 | 10.11 | 23.67 | 33.19 | 20.96 | 3.16 | 3.87 | -3.47 | 466.33 | |
| UK | 0.4565 | 0.4042 | 3.2787 | 0.8740 | 0.4754 | 1.5921 | 0.2751 | 0.3081 | 0.6005 | 0.27 |
| | 0.62 | 2.77 | 7.45 | 2.01 | 2.49 | 1.73 | 1.36 | 1.06 | 4.81 | |
| US | -9.4172 | 1.9197 | 6.1726 | 0.2924 | 0.3390 | 18.2047 | 0.4061 | -0.0577 | 0.5900 | 0.21 |
| | -15.98 | 6.83 | 40.83 | 1.75 | 3.64 | 3.57 | 3.51 | -1.20 | 23.57 | |

Table 8. Estimates of stock returns on conditional volatility, domestic and world downside risk

The dependent variable is monthly stock return $R_{it}$; the independent variables are defined as follows: $\widehat{\sigma}_{it}$ is the conditional volatility measured by the conditional standard deviation from the Threshold GED-GARCH (1,1)-M model. $VaR_{it}s$ and $VaR_t^{wxi}s$ are the local downside risk and world market downside risk defined as the minimum of daily stock return in the past 21 days as proposed by Bali et al. (2009), $VaR_t^{wxi}$ is the world downside risk and excludes the local $VaR_{it}$, which is the residual series obtained by regressing the $VaR_t^w$ on each local $VaR_{it}$. $Fear_t$ is the US fear index based on the St. Louis Fed stress index. $DY_t$ is the aggregate dividend yield, which serves as a control variable at time *t*. The $\delta, \varepsilon_{it}^2$ and $h_{it}$ are constant, shock squared, and conditional variance for market *i* using a threshold GED-GARCH (1,1)-M model. The original $VaR_{it}$s and $VaR_{it}^w$s are multiplied by -1 before running regressions. The values in the first row are the estimated coefficients; the values in the second row are the t-statistics. The significant levels at the 1%, 5%, and 10% level are 2.60, 1.97, and 1.65, respectively. $\bar{R}^2$ is the adjusted *R*-squared. The markets are Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK) and the United States (US).

| | $C$ | $\widehat{\sigma}_{it}$ | $VaR_{it-1}$ | $VaR_{it-1}^{wx1}$ | $Fear_{t-1}$ | $DY_{t-1}$ | $\delta$ | $\varepsilon_{it-1}^2$ | $\varepsilon_{t-1}^2 I_{t-1}^-$ | $\boldsymbol{\sigma_{t-1}^2}$ | $\bar{\boldsymbol{R}}^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CA | -2.9359 | 0.7603 | 5.9389 | 0.7337 | 0.6588 | 0.7189 | 9.5889 | 0.5027 | -0.3914 | 0.7914 | 0.26 |
| | -1.48 | 2.75 | 29.01 | 2.37 | 3.75 | 2.27 | 2.30 | 2.16 | -2.16 | 16.92 | |
| FR | 0.6092 | 0.4753 | 4.2670 | 1.9092 | 0.6223 | 0.7264 | 1.0853 | 0.5408 | -0.1678 | 0.7290 | 0.26 |
| | 1.08 | 5.08 | 31.14 | 5.49 | 2.08 | 5.09 | 1.57 | 2.65 | -0.99 | 25.46 | |
| GM | 0.6949 | 0.5400 | 5.3832 | 2.3832 | 0.3626 | 1.4885 | 1.6074 | 0.3631 | -0.1014 | 0.7015 | 0.33 |
| | 0.69 | 3.13 | 16.99 | 3.61 | 2.10 | 4.88 | 1.72 | 2.11 | -0.62 | 7.18 | |
| IT | -7.3115 | 0.9908 | 5.8131 | 2.7449 | 0.4040 | 0.9842 | 27.6652 | 0.3545 | -0.1170 | 0.6148 | 0.22 |
| | -1.36 | 1.70 | 64.61 | 10.99 | 4.25 | 18.13 | 3.04 | 1.35 | -1.11 | 12.32 | |
| JP | -1.2800 | 0.2841 | 4.9113 | 4.4638 | 0.1596 | 1.9213 | 112.2618 | 4.1138 | -1.2893 | 0.0400 | 0.31 |
| | -4.93 | 4.38 | 37.60 | 30.78 | 2.13 | 23.65 | 2.88 | 2.37 | -1.78 | 0.66 | |
| UK | -6.8424 | 1.2227 | 4.9317 | 1.7557 | 0.1739 | 0.9595 | 5.2276 | 0.2512 | -0.1586 | 0.8254 | 0.33 |
| | -4.79 | 3.22 | 47.79 | 9.61 | 3.09 | 7.75 | 3.74 | 2.07 | -1.78 | 47.45 | |
| US | -19.5827 | 4.5422 | 5.3516 | 4.0404 | 0.1928 | 2.1271 | 4.5336 | 0.0702 | -0.0327 | 0.7501 | 0.32 |
| | -4.96 | 3.62 | 21.61 | 8.38 | 1.77 | 6.43 | 6.28 | 2.58 | -1.40 | 107.69 | |

# Table 9. Robust estimates of stock returns on conditional volatility, domestic & world downside risks and stress index

The dependent variable is monthly stock return $R_{it}$; the independent variable $\widehat{\sigma}_{it}$ is the conditional volatility measured by the conditional standard deviation from the Threshold GED-GARCH (1,1)-M model. Different VaRs are generated from the bootstrapping procedure (Chen and Chiang, 2016). $VaR_{it}$s are the local downside risk ; $VaR_t^{wxi}$s are the world downside risk, which is the residual series obtained by regressing the $VaR_t^w$ on each local $VaR_{it}$. $Fear_t$ is the US fear index based on the St. Louis Fed stress index. $DY_t$ is the aggregate dividend yield, which serves as a control variable at time *t*. The $\delta$, $\varepsilon_{it}^2$ and $h_{it}$ are constant, shock squared, and conditional variance for market *i* using a threshold GED-GARCH (1,1)-M model. The original $VaR_{it}$s and $VaR_{it}^w$s are multiplied by -1 before running regressions. The values in the first row are the estimated coefficients; the values in the second row are the t-statistics. The significant levels at the 1%, 5%, and 10% level are 2.60, 1.97, and 1.65, respectively. $\bar{R}^2$ is the adjusted *R*-squared. The markets are Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK) and the United States (US).

| | $C$ | $\hat{\sigma}_{it}$ | $VaR_{it-1}$ | $VaR_{it-1}^{wxi}$ | $Fear_{t-1}$ | $DY_{t-1}$ | $\delta$ | $\varepsilon_{it-1}^2$ | $\varepsilon_{it-1}^2 I_{t-1}^-$ | $\boldsymbol{\sigma_{t-1}^2}$ | $\boldsymbol{\bar{R}^2}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CA | 2.3725 | 0.4099 | 2.0517 | 0.3149 | 2.6523 | 0.5582 | -0.1816 | 0.5846 | -0.3953 | 0.8906 | 0.32 |
| | 4.18 | 6.52 | 67.37 | 3.29 | 13.37 | 3.69 | -2.37 | 3.07 | -3.05 | 44.58 | |
| FR | -5.4616 | 1.0977 | 1.6923 | 0.5806 | 0.6296 | 1.8359 | 0.0737 | 0.2734 | -0.1281 | 0.8397 | 0.26 |
| | -3.42 | 5.05 | 17.12 | 2.41 | 2.59 | 5.35 | 0.27 | 3.55 | -1.65 | 30.64 | |
| GM | -5.1968 | 1.1463 | 1.8399 | 0.9472 | 1.5947 | 2.4620 | -0.0052 | 0.2516 | -0.1486 | 0.8750 | 0.28 |
| | -3.42 | 4.83 | 16.38 | 3.86 | 6.22 | 5.68 | -0.02 | 3.27 | -2.04 | 36.40 | |
| IT | -9.5948 | 1.3580 | 2.2583 | 0.5820 | 1.0032 | 1.3434 | 16.6974 | 0.3104 | -0.2423 | 0.6706 | 0.20 |
| | -1.98 | 2.22 | 47.07 | 5.35 | 8.09 | 15.01 | 3.14 | 1.81 | -1.76 | 20.68 | |
| JP | -1.5492 | 0.8336 | 1.4415 | 0.8632 | 1.3077 | 1.6719 | 1.1894 | 0.3066 | -0.0741 | 0.7560 | 0.28 |
| | -1.02 | 2.71 | 10.96 | 3.82 | 3.48 | 3.33 | 0.90 | 2.10 | -0.56 | 11.18 | |
| UK | -0.8650 | 0.7883 | 1.5126 | 0.5122 | 1.0074 | 0.6756 | 0.2672 | 0.3929 | -0.2790 | 0.7889 | 0.23 |
| | -0.57 | 4.20 | 14.38 | 2.05 | 4.73 | 1.72 | 1.17 | 2.86 | -2.04 | 16.74 | |
| US | -13.090 | 1.3895 | 1.6421 | 1.9055 | 1.4488 | 2.4346 | 13.9320 | 0.4125 | -0.1809 | 0.7860 | 0.26 |
| | -3.05 | 3.65 | 89.20 | 29.11 | 21.64 | 15.48 | 2.62 | 3.57 | -2.96 | 79.37 | |

Table 10. Robust estimates of stock returns on conditional volatility, domestic & world downside risks and the fear index

The dependent variable is monthly stock return $R_{it}$; the independent variable $\hat{\sigma}_{it}$ is the conditional volatility measured by the conditional standard deviation from the Threshold GED-GARCH (1,1)-M model. Different VaRs are generated from the bootstrapping procedure (Chen and Chiang, 2016). The $VaR_{it}$s are the local downside risk; $VaR_t^{wxi}$s are the world downside risk, which is the residual series obtained by regressing the $VaR_t^w$ on each local $VaR_{it}$. $Fear_t$ is measured by using the VIX index. $DY_t$ is the aggregate dividend yield, which serves as a control variable at time *t*. The $\delta$, $\varepsilon_{it}^2$ and $h_{it}$ are constant, shock squared, and conditional variance for market *i* using a threshold GED-GARCH (1,1)-M model. The original $VaR_{it}$s and $VaR_{it}^w$s are multiplied by -1 before running regressions. The values in the first row are the estimated coefficients; the values in the second row are the t-statistics. The significant levels at the 1%, 5%, and 10% level are 2.60, 1.97, and 1.65, respectively. $\bar{R}^2$ is the adjusted *R*-squared. The markets are Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK) and the United States (US).

| | $C$ | $\hat{\sigma}_{it}$ | $VaR_{it-1}$ | $VaR_{it-1}^{wxi}$ | $Fear_{t-1}$ | $DY_{t-1}$ | $\delta$ | $\varepsilon_{it-1}^2$ | $\varepsilon_{it-1}^2 I_{t-1}^-$ | $\sigma_{t-1}^2$ | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CA | -5.9595 | 1.3420 | 1.6645 | 0.5586 | 0.0880 | 1.5265 | 0.0084 | 0.2092 | -0.1297 | 0.8659 | 0.26 |
| | -3.77 | 9.04 | 17.32 | 1.91 | 3.01 | 3.09 | 0.34 | 4.04 | -2.79 | 34.13 | |
| FR | -9.7471 | 1.0383 | 1.9452 | 1.4612 | 0.2792 | 1.8219 | -0.1416 | 0.0861 | -0.0640 | 0.9577 | 0.26 |
| | -6.55 | 5.68 | 18.14 | 5.31 | 7.91 | 4.77 | -1.41 | 2.30 | -1.53 | 55.23 | |
| GM | -13.523 | 1.5628 | 1.6644 | 1.7159 | 0.3089 | 2.4637 | -0.3291 | 0.0347 | -0.0341 | 0.9964 | 0.27 |
| | -6.83 | 5.19 | 14.77 | 7.64 | 8.47 | 4.58 | -4.28 | 2.20 | -2.11 | 129.82 | |
| IT | -9.6798 | 1.1114 | 1.9805 | 0.7348 | 0.2041 | 1.3512 | 3.3187 | 0.1504 | -0.1187 | 0.8594 | 0.24 |
| | -8.59 | 9.60 | 19.45 | 3.51 | 5.98 | 6.74 | 6.40 | 6.79 | -2.38 | 32.50 | |
| JP | -14.844 | 1.8378 | 1.2799 | 1.0301 | 0.2097 | 0.6811 | 5.6670 | 0.3404 | -0.0272 | 0.2585 | 0.22 |
| | -14.57 | 10.63 | 26.62 | 8.16 | 13.16 | 3.53 | 21.06 | 5.27 | -0.55 | 4.55 | |
| UK | -8.9847 | 0.7403 | 1.7251 | 0.6661 | 0.3033 | 0.7207 | 9.1443 | 1.1412 | -0.9367 | 0.6006 | 0.25 |
| | -5.74 | 2.67 | 79.96 | 14.96 | 75.39 | 9.29 | 3.09 | 2.04 | -2.04 | 19.76 | |
| US | -9.6116 | 0.7455 | 1.2987 | 0.2651 | 0.2512 | 1.4573 | 2.9351 | 0.6867 | -0.4671 | 0.8864 | 0.30 |
| | -4.47 | 2.79 | 43.41 | 3.96 | 25.59 | 9.47 | 2.26 | 2.13 | -2.21 | 64.21 | |

Table 11. Robust estimates of excess stock returns of G7 markets on conditional volatility, domestic & world downside risks and the fear index

The dependent variable is monthly excess stock return $r_{it}$; the independent variable $\widehat{\sigma}_{it}$ is the conditional volatility measured by the conditional standard deviation from the Threshold GED-GARCH (1,1)-M model. Different VaRs are generated from the bootstrapping procedure (Chen and Chiang, 2016). $VaR_{it}s$ are the local downside risk , $VaR_t^{wxi}$s are the world downside risk, which is the residual series obtained by regressing the $VaR_t^w$ on each local $VaR_{it}$. $Fear_t$ is measured by using the US implied volatility (VIX index). $DY_t$ is the aggregate dividend yield, which serves as a control variable at time *t*. The $\delta$, $\varepsilon_{it}^2$ and $h_{it}$ are constant, shock squared, and conditional variance for market *i* using a threshold GED-GARCH (1,1)-M model. The original $VaR_{it}$s and $VaR_{it}^w$s are multiplied by -1 before running regressions. The values in the first row are the estimated coefficients; the values in the second row are the t-statistics. The significant levels at the 1%, 5%, and 10% level are 2.60, 1.97, and 1.65, respectively. $\bar{R}^2$ is the adjusted $R$-squared. The markets are Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK) and the United States (US).

| | $C$ | $\hat{\sigma}_{it}$ | $VaR_{it-1}$ | $VaR_{it-1}^{wxi}$ | $Fear_{t-1}$ | $DY_{t-1}$ | $\delta$ | $\varepsilon_{it-1}^2$ | $\varepsilon_{it-1}^2 I_{t-1}^-$ | $\sigma_{t-1}^2$ | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CA | -4.4463 | 2.7555 | 0.7194 | 0.4924 | 0.0927 | 0.4408 | -0.0005 | 0.0964 | -0.0963 | 0.9594 | 0.36 |
| | -4.97 | 6.26 | 14.27 | 5.13 | 5.47 | 2.11 | -0.03 | 2.90 | -2.81 | 55.31 | |
| FR | -4.6006 | 0.4218 | 1.5761 | 0.2931 | 0.2293 | 0.7364 | -0.1918 | 1.1435 | -0.8245 | 0.8088 | 0.24 |
| | -7.12 | 5.27 | 32.51 | 3.64 | 18.30 | 5.17 | -0.29 | 3.49 | -2.97 | 47.20 | |
| GM | -14.0527 | 1.6938 | 1.6869 | 1.6804 | 0.3031 | 2.5081 | -0.3025 | 0.0347 | -0.0303 | 0.9934 | 0.27 |
| | -6.02 | 4.92 | 15.01 | 6.88 | 8.04 | 4.67 | -3.48 | 2.46 | -2.24 | 129.96 | |
| IT | -12.1296 | 1.3279 | 2.4095 | 0.4329 | 0.1652 | 1.9689 | 6.8606 | 0.2342 | -0.2528 | 0.7811 | 0.18 |
| | -2.78 | 2.24 | 33.84 | 3.58 | 8.33 | 10.09 | 5.23 | 1.94 | -2.13 | 36.85 | |
| JP | -5.4757 | 0.2500 | 1.5632 | 1.6598 | 0.1695 | 2.0666 | 0.7601 | 0.9842 | -1.1869 | 0.8440 | 0.09 |
| | -9.51 | 5.16 | 109.41 | 32.77 | 14.92 | 10.44 | 0.62 | 2.94 | -3.16 | 48.56 | |
| UK | -8.5511 | 0.7208 | 1.7299 | 0.7361 | 0.2542 | 0.6293 | 1.8940 | 0.4394 | -0.0544 | 0.6252 | 0.28 |
| | -4.48 | 2.33 | 4.30 | 21.82 | 36.65 | 8.89 | 3.38 | 1.65 | -1.08 | 13.66 | |
| US | -4.5193 | 0.4210 | 1.9215 | 0.7423 | 0.2715 | 0.5138 | 0.0505 | 1.3242 | -1.2049 | 0.8401 | 0.32 |
| | -17.76 | 5.83 | 83.41 | 6.23 | 47.48 | 8.08 | 0.30 | 3.15 | -2.94 | 89.78 | |

Table 12. Robust estimates of excess stock returns of Latin American markets on conditional volatility, domestic & world downside risks and the fear index

The dependent variable is monthly excess stock return $r_{it}$; the independent variable $\widehat{\sigma}_{it}$ is the conditional volatility measured by the conditional standard deviation from the Threshold GED-GARCH (1,1)-M model. $VaR_{it}$s and $VaR_t^{wxi}$s are the local downside risk and world market downside risk defined as the minimum of daily stock return in the past 21 days as proposed by Bali et al. (2009). $VaR_t^{wxi}$ is the world downside risk excludes the local $VaR_{it}$, which is the residual series obtained by regressing the $VaR_t^{w}$ on each local $VaR_{it}$. $Fear_t$ is measured by using the US implied volatility (VIX index). $DY_t$ is the aggregate dividend yield served as a control variable at time *t*. The $\delta$, $\varepsilon_{it}^2$ and $h_{it}$ are constant, shock squared, and conditional variance for market *i* using a threshold GED-GARCH (1,1)-M model. The original $VaR_{it}$s and $VaR_{it}^{w}$s are multiplied by -1 before running regressions. The values in the first row are the estimated coefficients; the values in the second row are the t-statistics. The significant levels at the 1%, 5%, and 10% level are 2.60, 1.97, and 1.65, respectively. $\bar{R}^2$ is the adjusted *R*-squared. The markets are Argentine (AR), Brazil (BR), Chili (CL), Mexico (MX) and Pero (PR).

| | $C$ | $\hat{\sigma}_{it}$ | $VaR_{it-1}$ | $VaR_{it-1}^{wxi}$ | $Fear_{t-1}$ | $DY_{t-1}$ | $\delta$ | $\varepsilon_{it-1}^2$ | $\varepsilon_{it-1}^2 I_{t-1}^-$ | $\sigma_{t-1}^2$ | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AR | -4.4463 | 2.7555 | 0.7194 | 0.4924 | 0.0927 | 0.4408 | -0.0005 | 0.0964 | -0.0963 | 0.9594 | 0.36 |
| | -4.97 | 6.26 | 14.27 | 5.13 | 5.47 | 2.11 | -0.03 | 2.90 | -2.81 | 55.31 | |
| BR | -4.6006 | 0.4218 | 1.5761 | 0.2931 | 0.2293 | 0.7364 | -0.1918 | 1.1435 | -0.8245 | 0.8088 | 0.24 |
| | -7.12 | 5.27 | 32.51 | 3.64 | 18.30 | 5.17 | -0.29 | 3.49 | -2.97 | 47.20 | |
| CL | -3.6723 | 0.8416 | 2.6456 | 0.6524 | 0.0892 | 0.9746 | 0.0361 | 0.3485 | -0.0123 | 0.8790 | 0.28 |
| | -1.81 | 1.98 | 11.56 | 2.21 | 3.07 | 2.34 | 0.19 | 2.33 | -0.22 | 10.64 | |
| MX | -14.0527 | 1.6938 | 1.6869 | 1.6904 | 0.3031 | 2.5081 | -0.3025 | 0.0347 | -0.0303 | 0.9934 | 0.27 |
| | -6.02 | 4.92 | 15.01 | 6.88 | 8.04 | 4.67 | -3.48 | 2.46 | -2.24 | 129.96 | |
| PR | -12.1296 | 1.3279 | 2.4095 | 0.4329 | 0.1652 | 1.9689 | 6.8606 | 0.2342 | -0.2528 | 0.7811 | 0.18 |
| | -2.78 | 2.24 | 33.84 | 3.58 | 8.33 | 10.09 | 5.23 | 1.94 | -2.13 | 36.85 | |

Table 13. Robust estimates of excess stock returns of Asian markets on conditional volatility, domestic & world downside risks and the fear index

The dependent variable is monthly excess stock return $r_{it}$; the independent variable $\widehat{\sigma}_{it}$ is the conditional volatility measured by the conditional standard deviation from the Threshold GED-GARCH (1,1)-M model. $VaR_{it}$s and $VaR_t^{wxi}$s are the local downside risk and world market downside risk defined as the minimum of daily stock return in the past 21 days as proposed by Bali et al. (2009). $VaR_t^{wxi}$ is the residual series obtained by regressing the $VaR_t^w$ on each local $VaR_{it}$. $Fear_t$ is measured by using the US implied volatility (VIX index)/ $DY_t$ is the aggregate dividend yield, which serves as a control variable at time *t*. The $\delta$, $\varepsilon_{it}^2$ and $h_{it}$ are constant, shock squared, and conditional variance for market *i* using a threshold GED-GARCH (1,1)-M model. The original $VaR_{it}$s and $VaR_{it}^w$s are multiplied by -1 before running regressions. The values in the first row are the estimated coefficients; the values in the second row are the t-statistics. The significant levels at the 1%, 5%, and 10% level are 2.60, 1.97, and 1.65, respectively. $\bar{R}^2$ is the adjusted *R*-squared. The markets are: China (CN), Hong Kong (HK), South Korea (KO), Malaysia (MA), Singapore (SG), Thailand (TH) and Taiwan (TW).

| Markets | $C$ | $\hat{\sigma}_{it}$ | $VaR_{it-1}$ | $VaR_{it-1}^{wxi}$ | $Fear_{t-1}$ | $DY_{t-1}$ | $\delta$ | $\varepsilon_{it-1}^2$ | $\sigma_{t-1}^2$ | $\bar{R}^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| CN | -3.0939 | 0.1637 | 1.3426 | 1.1651 | 0.1944 | 1.5369 | 5.6122 | 0.4211 | 0.7981 | 0.01 |
| | -4.06 | 2.45 | 13.48 | 8.12 | 15.39 | 10.76 | 0.72 | 1.74 | 17.56 | |
| HK | -6.3952 | 1.3077 | 2.4147 | 2.2906 | 0.1241 | 1.0869 | 12.0401 | 0.2305 | 0.5809 | 0.22 |
| | -2.08 | 3.91 | 20.57 | 5.65 | 3.39 | 2.38 | 3.62 | 4.79 | 5.94 | |
| ID | -1.5654 | 0.3244 | 3.3039 | 0.5386 | 0.2402 | 1.6896 | 4.1803 | 0.2954 | 0.6813 | 0.33 |
| | -0.81 | 1.73 | 16.37 | 1.64 | 3.23 | 2.89 | 2.27 | 3.47 | 8.38 | |
| KO | -4.9617 | 0.3960 | 2.6554 | 2.3361 | 0.3109 | 2.9336 | 2.0472 | 0.2042 | 0.7895 | 0.18 |
| | -3.01 | 1.96 | 11.49 | 6.30 | 5.93 | 3.09 | 1.87 | 5.01 | 20.86 | |
| MA | -0.7191 | 0.2989 | 2.8402 | 1.9767 | 0.1896 | 0.5349 | 1.1872 | 0.2336 | 0.8256 | 0.09 |
| | -0.84 | 2.78 | 17.94 | 17.27 | 8.78 | 2.30 | 1.02 | 2.37 | 14.59 | |
| SG | -2.8258 | 0.3939 | 2.8876 | 0.3710 | 0.0143 | 1.9145 | 37.9940 | 0.5127 | 0.5451 | 0.26 |
| | -1.36 | 2.07 | 73.40 | 9.59 | 3.70 | 27.66 | 3.15 | 1.68 | 19.73 | |
| TH | -1.7892 | 0.8003 | 3.1678 | 2.0528 | 0.1079 | 0.9646 | 1.0130 | 0.1629 | 0.8065 | 0.32 |
| | -1.24 | 3.00 | 14.20 | 6.14 | 2.44 | 2.18 | 1.95 | 3.62 | 19.06 | |
| TW | -2.4992 | 0.4381 | 3.1308 | 3.0670 | 0.2795 | 1.4710 | 0.6167 | 0.0357 | 0.9470 | 0.25 |
| | -1.06 | 1.81 | 16.30 | 8.07 | 3.77 | 2.84 | 1.47 | 2.67 | 74.92 | |

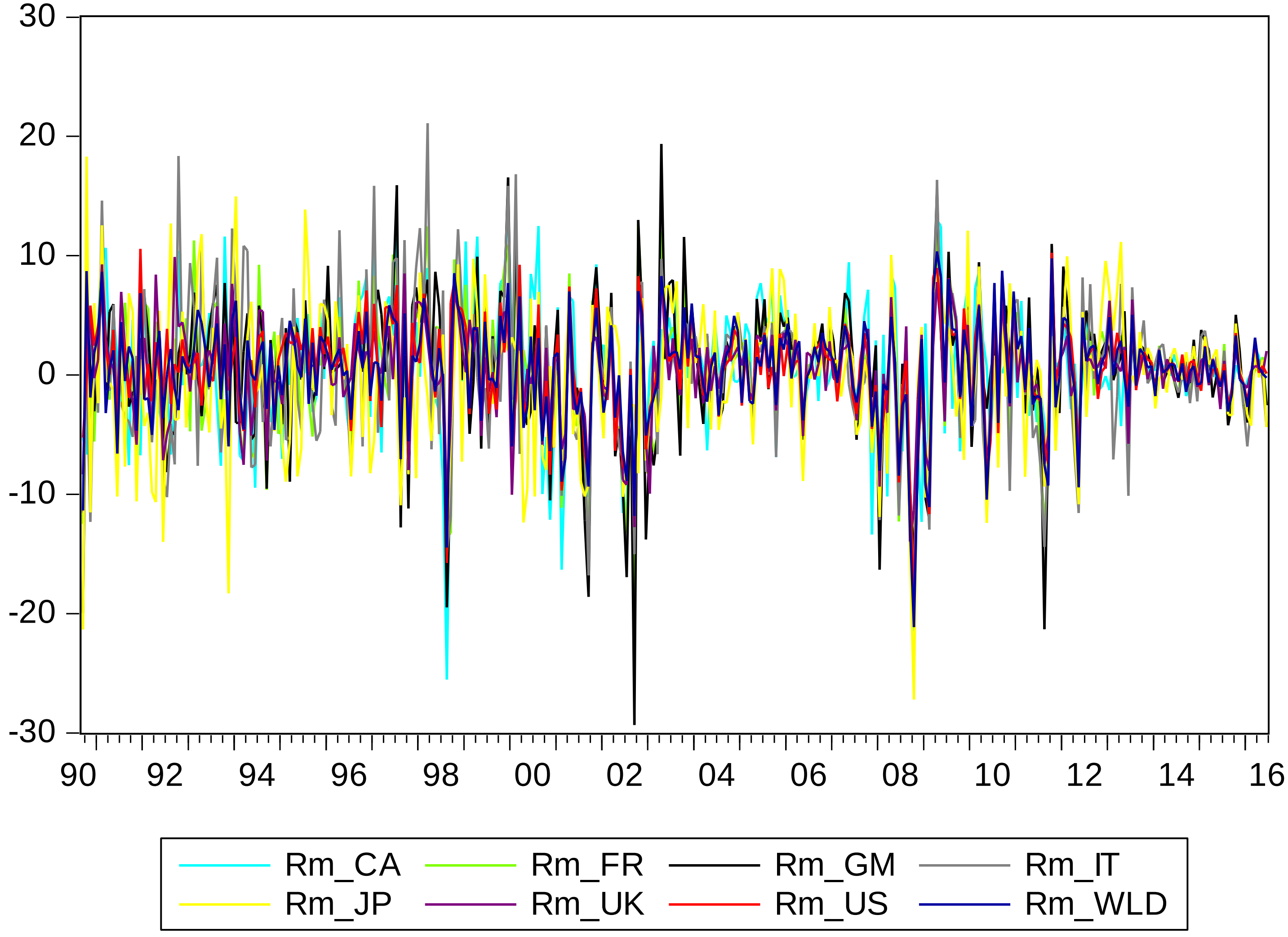


Fig. 1. Time series plots of stock returns for G7 and World markets

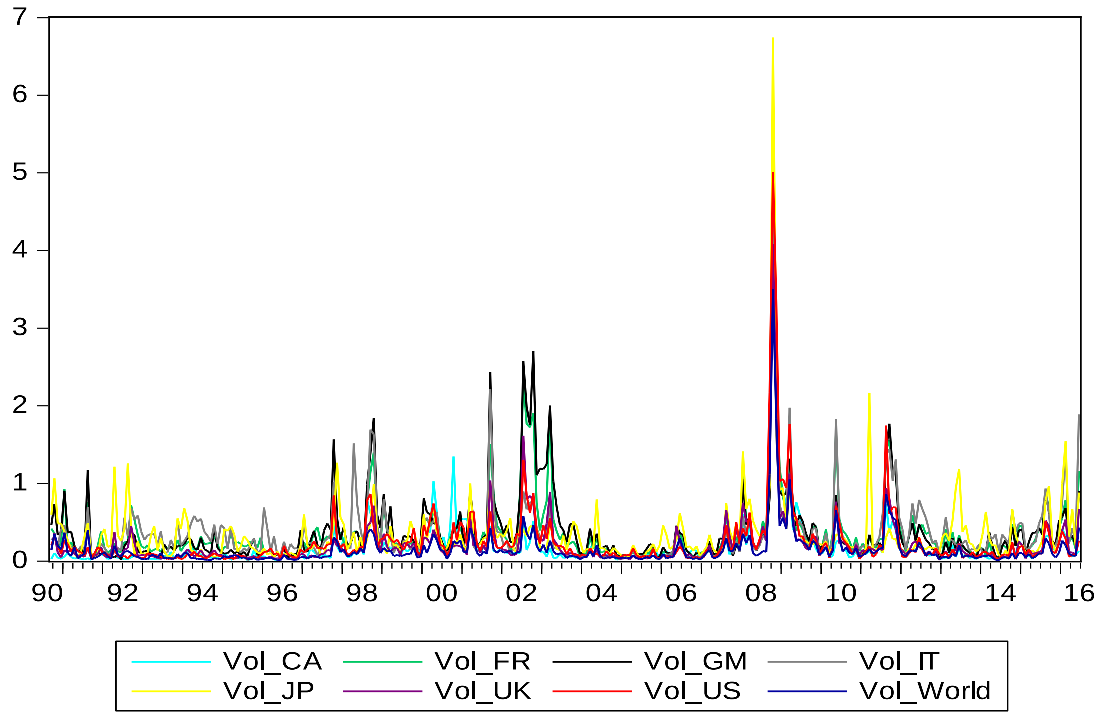


Fig. 2.A. Time series plots of volatility of stock returns for G7 and World markets

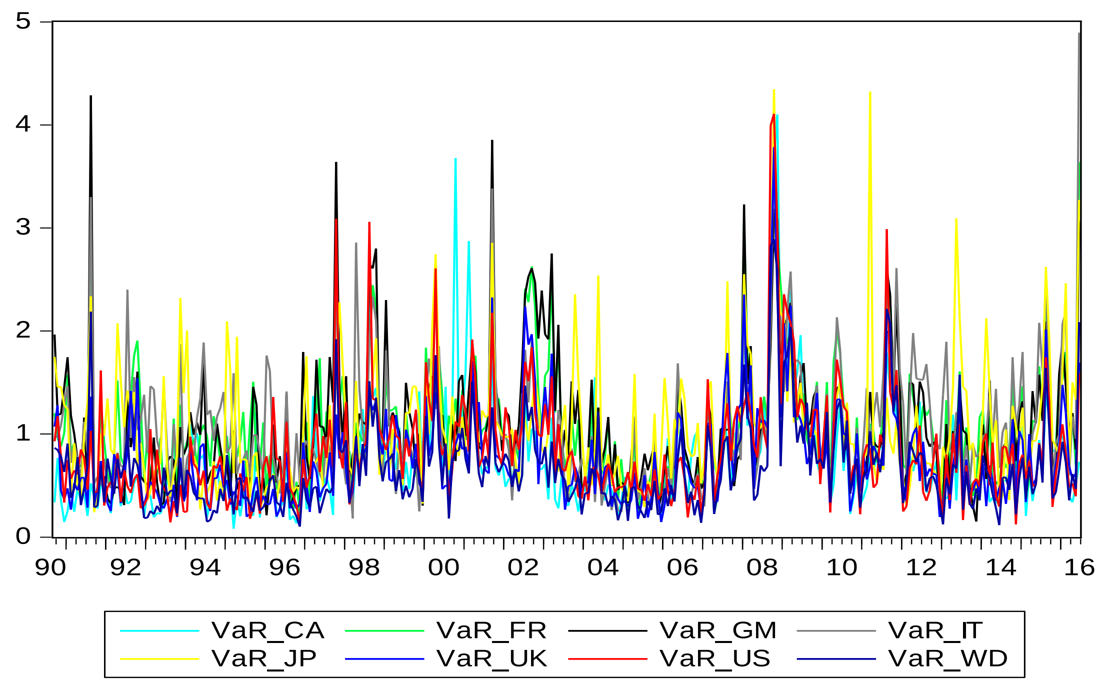


Fig. 2.B. Time series plots of Absolute downside stock returns for G7 and World markets

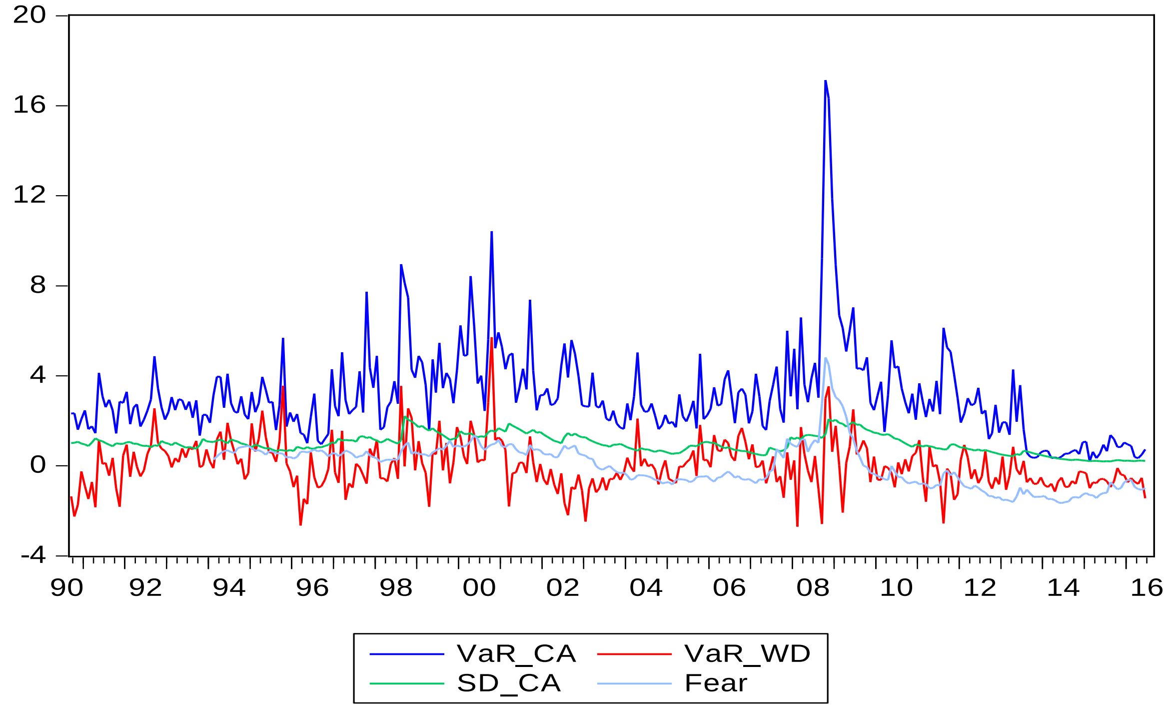


Fig. 3A. Time series plots of CA downside risk, world downside risk, CA conditional $\hat{\sigma}_t$ and the US fear index

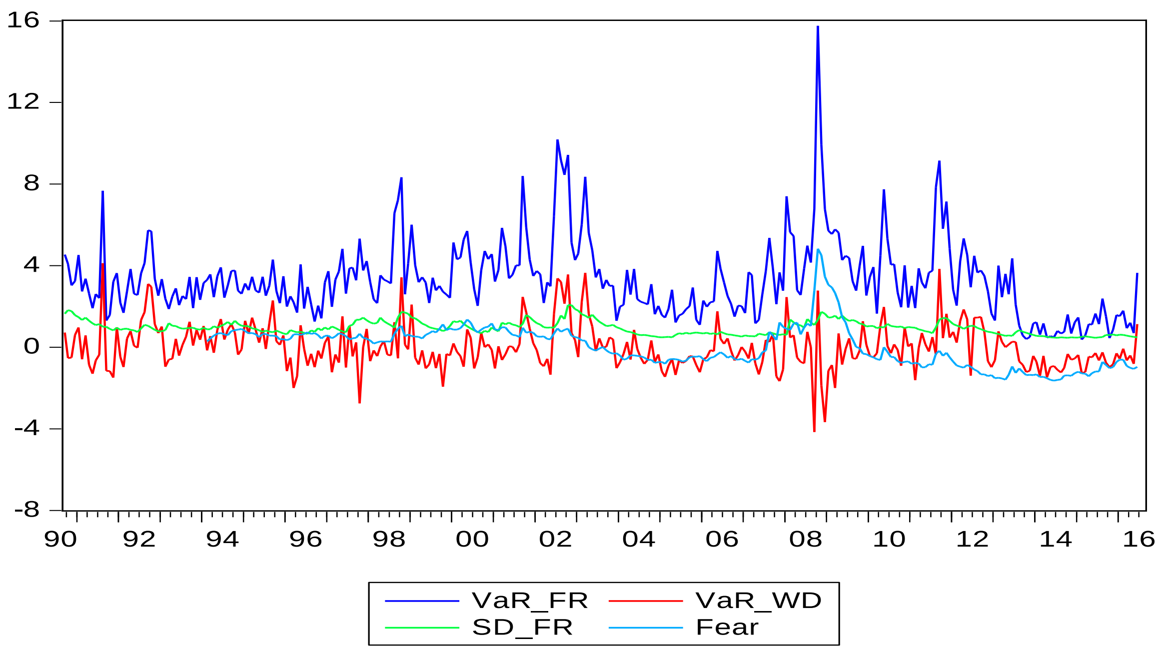


Fig. 3B. Time series plots of FR downside risk, world downside risk, FR conditional $\hat{\sigma}_t$ and the US fear index

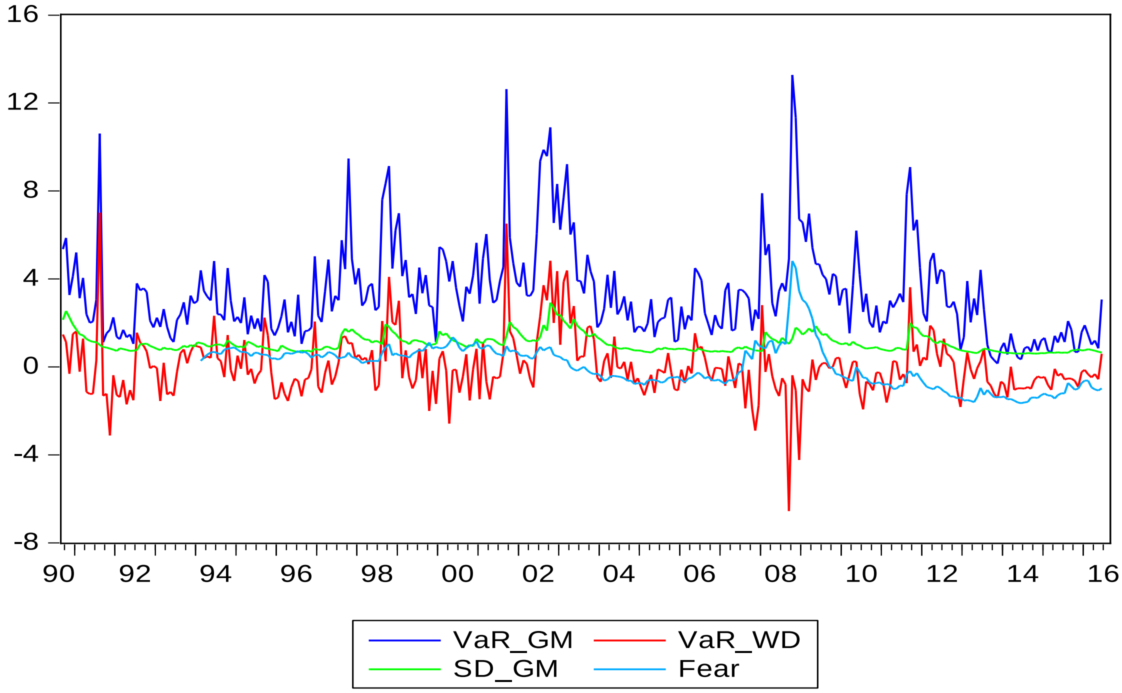


Fig. 3C. Time series plots of GM downside risk, world downside risk, GM conditional $\hat{\sigma}_t$ and the US fear index

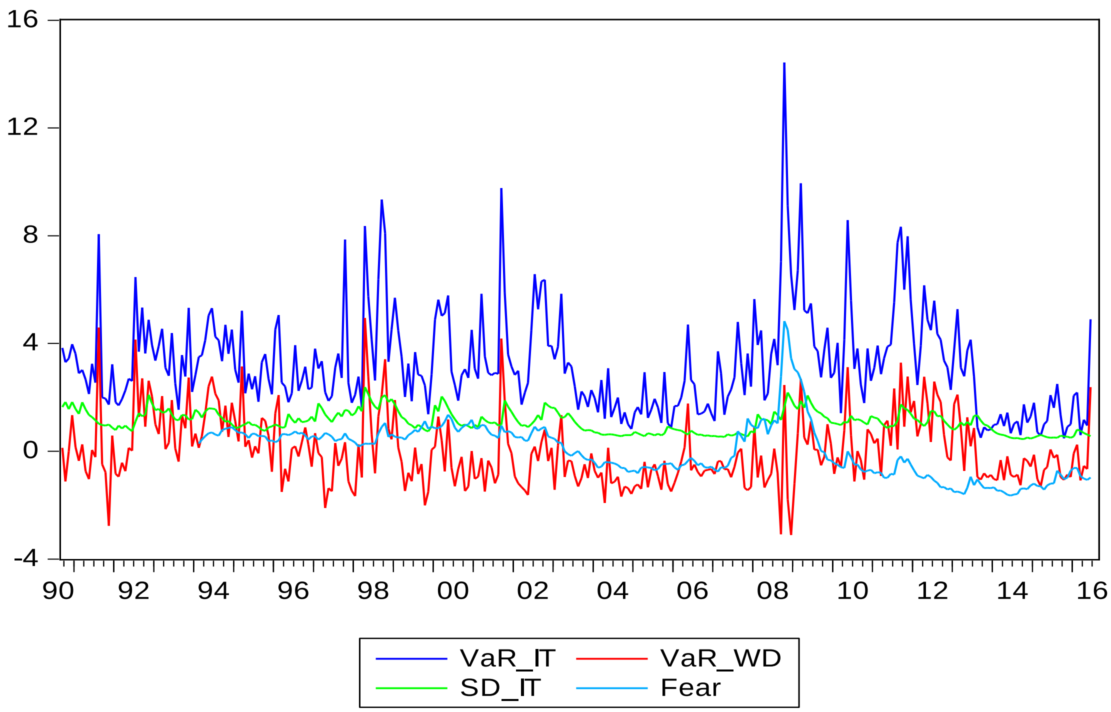


Fig. 3D. Time series plots of IT downside risk, world downside risk, IT conditional $\hat{\sigma}_t$ and the US fear index

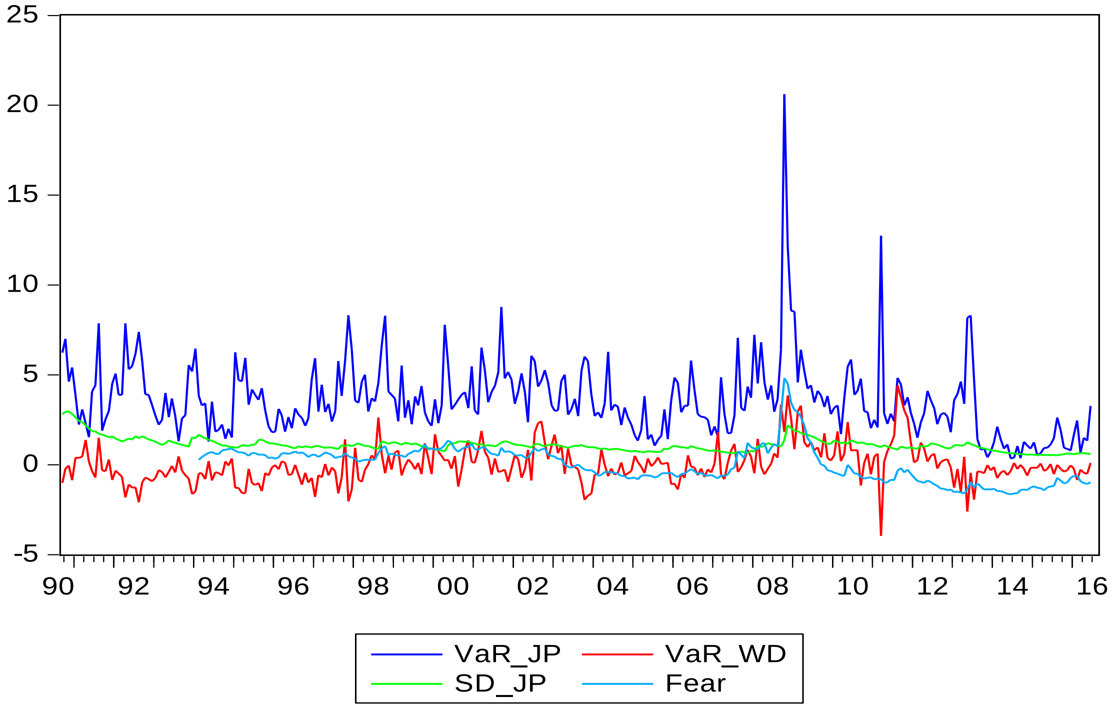


Fig. 3E. Time series plots of JP downside risk, world downside risk, JP conditional $\hat{\sigma}_t$ and the US fear index

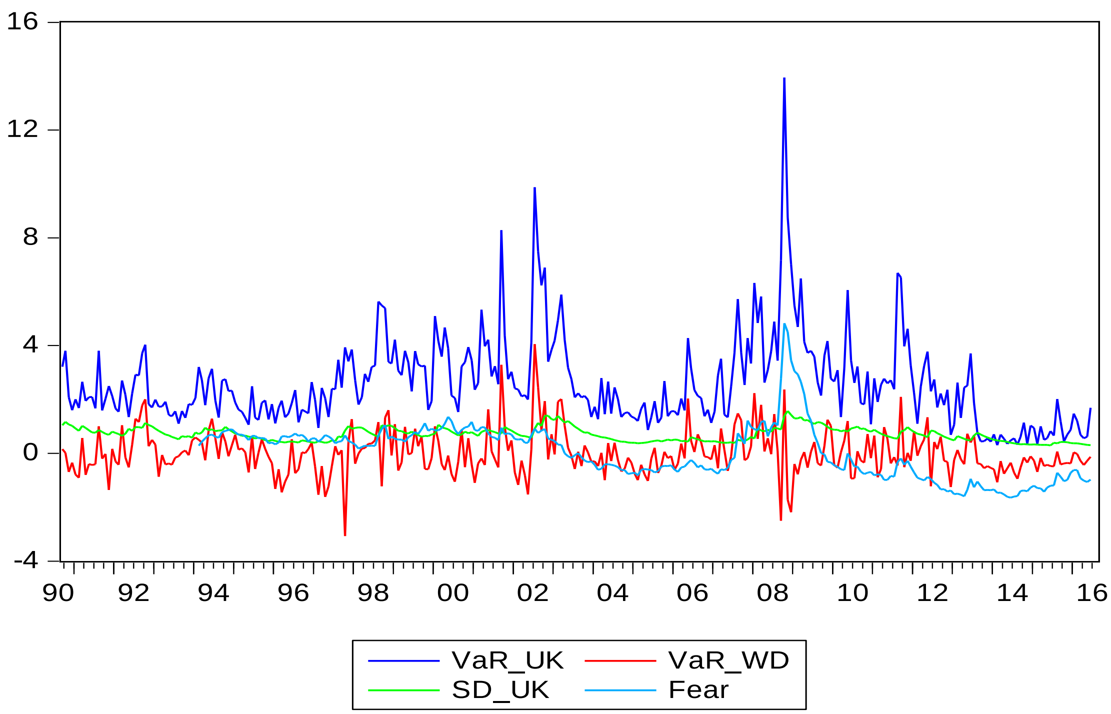


Fig. 3F. Time series plots of UK downside risk, world downside risk, UK conditional $\hat{\sigma}_t$ and the US fear index

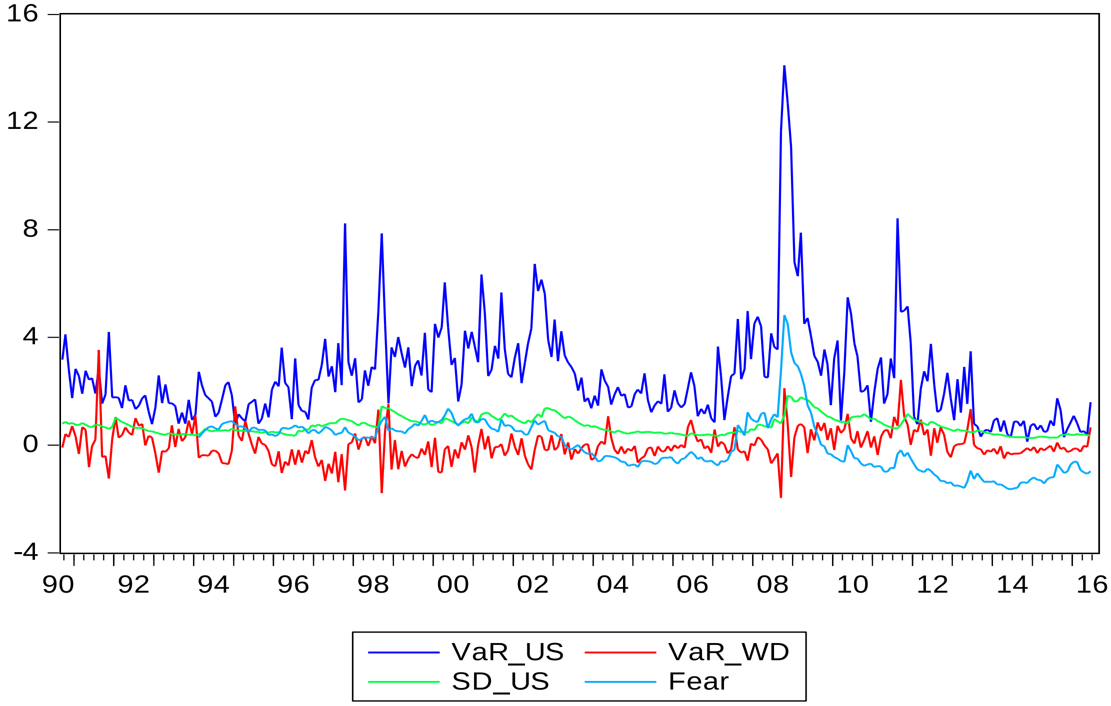


Fig. 3G. Time series plots of US downside risk, world downside risk, US conditional $\hat{\sigma}_t$ and the US fear index