Global Risk Aversion Spillover Dynamics and Investors' Attention Allocation

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Abstract

This paper investigates market-wide risk aversion in an international setting. Particularly, this empirical study evaluates risk aversion spillover dynamics as an uncertainty transmission mechanism for the period 2000-2015 to reveal if there has been a significant change in these dynamics when markets are going through turbulent periods. As a plausible proxy for risk aversion, variance risk premium (VRP) is computed through the difference between expected variances under risk-neutral and physical measures for seven markets studied: United States, United Kingdom, Germany, France, Netherlands, Switzerland and Japan. Effects of a shock to U.S. VRP on the other markets' VRPs are evaluated through Generalized Forecast Error Variance Decomposition. Results show that risk aversion spillovers from U.S. to other markets are stronger while the U.S. is going through turbulent periods confirming the intuition that investors are more focused on incidents in the turbulent market. Markets become more connected in terms of sentiments when a country is unexpectedly hit by a major crisis, limiting diversification opportunities.

JEL Classification: D8, F36, G14, G15.

Keywords: Investor sentiment, Risk aversion spillovers, Variance risk premium, Generalized forecast error variance decomposition, Investors' attention allocation, Financial crises.

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1 Introduction

Following the 2007 subprime crisis, empirical and theoretical studies on contagion have regained attention. Early studies have conceived the contagion phenomenon in a very broad sense, as being any cross-country transmission of shocks. Fundamentals-based explanations of contagion dominated this generation of studies. Some papers argued that shocks are transmitted through trade links that connect different countries (Glick and Rose, 1999), while several others emphasize the role of financial linkages in propagation of crises (Kaminsky and Reinhart, 2000). Another strand of literature adopted a restrictive definition, confining the contagion phenomenon to excessive cross-country correlations, beyond what can be explained through trade and credit channels. Behavioral arguments are employed to explain these excessive correlations. The role of a risk premium channel is stressed within these behavioral arguments. When one market is hit by an adverse shock, investors' risk aversion increases. This shift in investor sentiment leads to an upward adjustment of risk premia on all risky assets (Kumar and Persaud, 2002). Longstaff (2010) finds that negative shocks to subprime asset-backed collateralized debt obligations market are propagated to other markets primarily through time-varying risk premia. Baker *et al.* (2012) suggest that investor sentiment itself is contagious and that international capital flows constitute an important mechanism by which sentiment spreads across markets. An interesting paper by Mondria and Quintana-Domeque (2013) suggest that sudden shifts in market confidence cause contagion. They empirically find that when a region is hit by a financial crisis, investors optimally relocate their attention to this region and that this attention relocation leads to volatility transmission from the turbulent region to the others. The less anticipated the crisis is, the more focused the investors would be on the turbulent region, giving rise to a higher contagion.

Related to the above studies hinging on the risk premium channel to explain volatility spillovers, this paper investigates market-wide risk aversion in an international setting. As a plausible proxy for risk aversion, variance risk premium (VRP) is computed through the difference between expected variances under risk-neutral and physical measures. The risk-neutral measures are readily provided by VIX-type implied volatility indexes for seven markets studied: United States, United Kingdom, Germany, France, Netherlands, Switzerland and Japan. The physical measures are based on range-based volatilities that are computed using daily stock index data. The risk-neutral measure provides us with the implied volatility that captures investors' perception on the uncertainty for the upcoming month whereas the physical measure gives the expected level of actual volatility for the same period. This time-varying risk aversion is a noteworthy factor behind fluctuations in the risk premia. It is thus worth to analyze risk premium spillovers as an important aspect related to the risk premium channel.

This empirical study evaluates risk aversion spillover dynamics for the period 2000-2015. This period is divided into five subperiods covering tranquil or turbulent states in the U.S. and European financial markets. For each period, risk aversion spillovers are studied as an uncertainty transmission mechanism to reveal if there has been a significant change in the spillover dynamics especially around subprime mortgage crisis. Effects of a shock to U.S. VRP on the other markets' VRPs are evaluated through Generalized Forecast Error Variance Decomposition (GFEVD) developed by Pesaran and Shin (1998). Results show that risk aversion spillovers from U.S. to other markets are stronger while the U.S. is going through turbulent periods confirming the intuition that investors are more focused on incidents in the turbulent market. Markets become more connected in terms of sentiments when a country is unexpectedly hit by a major crisis, limiting diversification opportunities when investors are most in need of the gains stemming from diversification.

The remainder of the paper is as follows: The second section introduces the construction of volatility measures. Range-based volatilities, physical and risk-neutral measures of expected measures that are used to estimate VRPs as a proxy for market-wide risk aversion levels are shortly discussed here. Data used for the analysis is given in the third section. The fourth section presents the empirical methodology discusses the empirical results. The fifth section concludes.

2 Range-Based Volatility and Variance Risk Premia

2.1 Range-Based Volatilities

In the literature several volatility estimators are employed ranging from the classical close-to-close estimator based on daily returns to realized volatilities derived from intraday prices. While realized volatility measures provide more accurate volatility estimates, daily data based volatility estimators are still being widely used as it may be hard (or impossible in some cases) to obtain intraday data. Range-based volatility estimators provide an intermediate solution to this dilemma. We do not need intraday data to estimate range-based volatilities, and range-based volatilities are far better estimators of volatilities when compared to the close-to-close estimator.

Garman and Klass (1980) proposed a volatility estimator based on the opening, closing, highest and lowest prices information. As the intraday high-low price range provides additional information regarding volatility, Garman-Klass estimator constitute a more efficient estimator than the close-to-close estimator that is based on two arbitrary points in price series. Garman and Klass suggest the following estimator that may be applied to compute daily volatilities:

$$\sigma_t = \sqrt{0.5\left[\log\left(\frac{H_t}{L_t}\right)\right]^2 - [2\log 2 - 1]\left[\log\left(\frac{C_t}{O_t}\right)\right]^2} x100 \tag{1}$$

where O_t is the opening price, C_t is the closing price, H_t is the highest price and L_t is the lowest price of the t^{th} trading day.

2.2 Variance Risk Premia

Investors do not only require compensation for volatility of returns. It is now well established that investors demand additional compensation for risk when they perceive that the danger of big shocks to the state of the economy is high[1]. VRP is the compensation for variance risk that stems from the randomness of return variances. It is shown to be procyclical, increasing in market downturns that are characterized by high volatility and high risk aversion. As such, it is used to capture investors' attitudes toward uncertainty (Bollerslev *et al.*, 2011; Bakshi and Madan, 2006). If estimated appropriately, VRP may constitute a good proxy for the risk aversion.

VRP is defined as the difference in expected variances under risk-neutral and physical measures over the $[t, t+n]$ time interval[2]:

[1]See, for example, Bollerslev *et al.*, 2009; Drechsler and Yaron, 2011

[2]See, for example, Demeterfi *et al.*, 1999; Britten-Jones and Neuberger, 2000; Jiang and Tian, 2005; Carr and Wu, 2008

$$VRP_{t,t+n} = \mathrm{E}^{\mathbb{P}}(Var_{t,t+n} \mid \mathcal{F}_t) - \mathrm{E}^{\mathbb{Q}}(Var_{t,t+n} \mid \mathcal{F}_t) \tag{2}$$

where $\mathrm{E}^{\mathbb{P}}(\cdot)$ and $\mathrm{E}^{\mathbb{Q}}(\cdot)$ denote the time t expectation operator under the physical and risk-neutral measures respectively. These measures are not directly observable. Several methods have been developed to approximate them.

To make the distribution closer to normality $VRP_{t,t+n}$ may be expressed in its logarithmic form:

$$\log\left(VRP_{t,t+n}\right) = \log\left(\mathrm{E}^{\mathbb{P}}(Var_{t,t+n} \mid \mathcal{F}_t)\right) - \log\left(\mathrm{E}^{\mathbb{Q}}(Var_{t,t+n} \mid \mathcal{F}_t)\right) \tag{3}$$

The risk-neutral expectation of the future variance $\left(\mathrm{E}^{\mathbb{Q}}\right)$ in the above equation is measured based on option prices, as a weighted average, or integral, of a continuum of a fixed n-maturity options:

$$\mathrm{E}_t^{\mathbb{Q}}(Var_{t,t+n}) = \mathrm{IV}^*_{t,t+n\Delta} = 2\int_0^\infty \frac{C(t+n,K) - C(t,K)}{K^2} dK \tag{4}$$

where $C(t,K)$ denotes the price of a European call option maturing at time t with strike price K.

The physical measure $\left(\mathrm{E}^{\mathbb{P}}\right)$ is approximated through using realized variance measures that are derived from the underlying security prices. Methods used to compute the physical expectation vary in practice. While Carr and Wu (2008) use simply the ex-post forward realized variance to substitute for the expected return variance Drechsler and Yaron (2011) use lagged implied and realized variances to forecast it. Todorov (2009) estimates the physical measure in a semi-parametric framework. Bollerslev *et al.* (2009) use a multifrequency autoregression with multiple lags and Zhou (2010) uses a simple autoregression with twelve lags to estimate the objective expectation of the return variance.

In this paper, the expected variance under the physical measure is estimated through a Heterogeneous Autoregressive (HAR) model that is proposed by Corsi (2009). The HAR model is a straightforward unfolding of Heterogeneous Autoregressive Conditional Heteroscedasticity (HARCH) models analysed earlier in Müller *et al.* (1997). An HAR model can be specified as a multi-component variance model in which the conditional variance is parametrized as a sum of variance components over different horizons. In its simplest form, an HAR model is estimated through the sum of daily, weekly and monthly variances

$$\sigma_t^2 = \beta_D \sigma_{t-1}^2 + \beta_W \sigma_{t-5:t-1}^2 + \beta_M \sigma_{t-22:t-1}^2 \tag{5}$$

where

$$\sigma_{t+1-k:t}^2 = \frac{1}{k} \sum_{j=1}^{k} \sigma_{t-j}^2$$

and where the coefficients β_D, β_W, β_M are determined through an OLS estimation.

Given that the logarithmic daily variances are approximately unconditionally normally distributed, Equation 5 is expressed in its logarithmic form following Andersen *et al.* (2007):

$$\log\left(\sigma_t^2\right) = \beta_D \log\left(\sigma_{t-1}^2\right) + \beta_W \log\left(\sigma_{t-5:t-1}^2\right) + \beta_M \log\left(\sigma_{t-22:t-1}^2\right) \tag{6}$$

where

$$\log(\sigma_{t+1-k:t}^2) = \frac{1}{k} \sum_{j=1}^{k} \log(\sigma_{t-j}^2)$$

3 Data

In this paper VRP series are computed for 15 years, from February 2000 to February 2015, for seven markets studied: United States, United Kingdom, Germany, France, Netherlands, Switzerland and Japan. As mentioned above, estimation of the VRP series that I employ to approximate risk aversion levels for each market is based on risk-neutral and physical measures of future index volatilities.

The risk-neutral measures, the options-implied volatilities, are readily provided by Datastream. Implied volatility series are computed based on index options covering out-of-the-money strike prices for near and next-term maturities following the widely used VIX methodology of the Chicago

Board of Options Exchange [3]. This model-free implied volatility is proven to be a better approximation to the one month ahead risk-neutral expectation of the integrated volatility than the Black-Scholes implied volatility. Implied volatility series were provided in annualized measures. In order to obtain daily estimates, implied volatility measures are divided by $\sqrt{365}$. The daily-standardized estimates of the expected one-month ahead volatility under the physical measure are obtained based on the logarithmic HAR model given in Equation 6.

Japanese market is closed before the other markets are opened. Data is adjusted to cope with this issue: for the estimation, Japanese market data is led by one day.

Summary statistics of the constructed volatility series for each market are provided in Table 1. For all of the financial markets, akin to the empirical literature, risk-neutral measures are higher than the physical measures of expected volatility during almost all the period. VRP series have thus negative values. To represent the level of risk aversion, these series are multiplied by -1. Logarithmic measures of risk aversion levels are fairly close to normality, although some of the series are slightly right skewed and leptokurtic.

Figure 1 shows risk aversion series used in the estimation. Data covers five subperiods of alternating volatility and risk aversion levels. The first period spans from February 2000 to September 2003 and it is dominated by the negative consequences of the dot-com bubble burst and the 9/11 attacks in the United States. A relatively stable period follows from October 2003 to July 2007. The most interesting periods start by August 2007 and concern the recent financial crisis. During the second half of 2007, negative effects of the decline in housing prices started to be felt in the overall U.S. economy, and this led to a panic in the stock and foreign exchange markets by the beginning of 2008. With the collapse of Lehman Brothers in September 2008, the crisis is remarkably deepened, and it gained a global character through a drastic decrease in global liquidity by the first half of 2009. Between January 2010 and July 2012, European Sovereign Debt Crisis troubled especially the Euro-area countries. The last period starts by August 2012 and it is characterized by relative stability.

[3] This method is developed by Demeterfi et al. (1999).

4 Empirical Strategy and Results

The empirical analysis is based on GFEVD that is obtained through a Vector Autoregressive VAR) model formulated as follows:

$$X_t = \sum_{p=1}^{p} \Phi_p X_{t-p} + \epsilon_t \tag{7}$$

where Y_t, Y_{t-1},..., Y_{t-p} are (8×1) vectors containing logarithmic measures of VRPs of the seven markets studied as estimated through Equation 3, p is the VAR order, Phi_1, Phi_2,..., Phi_p are (8×8) matrices containing the VAR parameters to be estimated, and ϵ_t is a vector of innovations. In the empirical analysis, VAR orders are determined based on Akaike Information Criterion.

Once the covariance stationarity condition is satisfied the above VAR model can be rewritten in an infinite order moving average representation:

$$X_t = \sum_{j=0}^{\infty} \Psi_j \epsilon_{t-j} \tag{8}$$

where the (8×8) moving average coefficient matrices, Ψ_j obey the recursion $\Psi_j = \Phi_1 \Psi_{j-1} + \Phi_2 \Psi_{j-2}, ... + \Phi_p \Psi_{j-p}$ with Ψ_0 an identity matrix.

These moving average coefficients are used to generate impulse response functions (IRF) and forecast error variance decompositions (FEVD) to study the impact of a hypothetical shock on the dynamics of the system. When VAR innovations are contemporaneously correlated Cholesky factorization is generally employed to obtain orthogonalized innovations. However, in this case, IRF and FEVD results highly depend on the ordering of the variables. Pesaran and Shin (1998) proposes a solution to this problem through Generalized VAR framework that allows correlated shocks. In this framework Generalized IRF is defined as follows:

$$GIRF_i(h) = \sqrt{\sigma_{ii}} \Psi_h \Sigma e_i \tag{9}$$

where Σ is the variance-covariance matrix of residuals, and e_i is the selection vector with one at a position i and zeros otherwise. The GIRF thus defined allows us to assess the effect of one standard error shock to the i^{th} equation at time t on expected values of vector X at horizon $t+h$. The corresponding GFEVD captures the share of the h-step ahead forecast error variance of variable j which is due to the innovations in variable i:

$$GFEVD_{j,i}(h) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{h} \left(e_j' \Psi_h \Sigma e_i\right)^2}{\sum_{h=0}^{h} e_j' \Psi_h \Sigma \Psi_h' e_j} \tag{10}$$

GFEVDs are estimated for each of the five subperiods described in the data section. All the GIRFs are fully stabilized at 30 lags. Thus, GFEVDs are estimated for 30 days horizon. As the shocks are not orthogonalized, forecast error variance decompositions for each response variable do not necessarily sum to one. In order to make the results comparable, the sums of contributions of impulse variables to the variance of forecast error of each response variable are normalized to one.

Main empirical results are reported in Table 2, Table 3, Figure 2, and Figure 3. Table 2 and Figure 2 contain the percentage contributions of risk aversion of the U.S. market (as represented by the -log of VRP of the S&P 500) to the variances of forecast error of each of the other financial markets. Periods one to five heading the columns of the table stand for the subperiods of the data sample. The importance of risk aversion spillovers from U.S. to other markets is lower in the second period when compared to the first period which marked by a financial turbulence due to the dot-com bubble burst. All the markets seem to be focused on the U.S. market with the subprime crisis: except for Japan, the weights of the risk aversion spillover effects from U.S. are more than doubled (even tripled) in the third period, compared to the second period. These high levels of weights are sustained in the following periods.

Another interesting regularity is presented in Table 3 and Figure 3. Shares of forecast error variances due to shocks to each market itself are provided here. For all of the markets, there is a substantial decrease in the importance of the own shocks in GFEVDs in the third period which is marked by the outbreak of the subprime crisis in U.S. after a long period of tranquility. With the crisis, all the markets become more prone to risk aversion spillovers from other markets, possibly because investors allocate more attention and become more sensitive to what is going on in all over the world. That is to say, markets become more connected in terms of sentiments when a country is unexpectedly hit by a major crisis. By the end of the subprime crisis, investors in Japan are tranquilized fast: pre-crisis levels are attained by the fourth period in Japan. Other markets suffer from the negative effects of the European sovereign debt crisis in the fourth period. Averted investors in these markets continue to allocate more attention to the rest of the world. The negative effects of the debt crisis continue to hold more or less even in the fifth period for Euro-zone countries while pre-subprime crisis levels are attained in the U.K. and Switzerland. Japan is stabilized faster than the U.K. and Switzerland, possibly because the U.K and Switzerland are more closely connected to Euro-zone countries.

5 Conclusion

In this paper, risk aversion spillover dynamics is studied for seven financial markets from 2000 to 2015 through a Generalized Forecast Error Variance Decomposition analysis. Data sample is divided into five subperiods covering tranquil or turbulent states in the U.S. market. It is found that risk aversion spillovers from U.S. to other markets get much stronger starting from the third period while the U.S. is going through turbulent periods confirming the intuition that investors shift their attention on incidents in the turbulent market. Results also show that, with the outbreak of the subprime crisis in U.S., all the markets become more prone to risk aversion spillovers from the other markets. Markets become more connected in terms of sentiments when a country is unexpectedly hit by a major crisis, limiting diversification opportunities when investors are most in need of the gains stemming from diversification. Further interesting results are obtained concerning the European sovereign debt crisis. The debt crisis has only regional effects on investors with Japan remained unaffected. The negative effects of debt crisis on investors' attention allocation last longer for Euro-zone countries than for the U.K. and Switzerland. This shows that investors' focus is determined by a complex amalgam of fundamental and sentimental factors.

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Table 1: Descriptive Statistics

Market	Series	Mean	Median	Min	Max	Std. Dev.	Skewness	Exc. Kurt.
	$\log(E^{\mathbb{P}})$	-0.3680	-0.4286	-1.2856	1.1631	0.4042	0.7021	0.3505
U.S.	$\log(E^{\mathbb{Q}})$	0.0159	-0.0129	-0.6584	1.4428	0.3704	0.6112	0.2376
	-log(VRP)	0.3839	0.3766	-0.1791	1.0137	0.1565	0.2528	0.3744
	$\log(E^{\mathbb{P}})$	-0.2976	-0.3402	-1.1676	1.0549	0.3979	0.5113	-0.1451
U.K.	$\log(E^{\mathbb{Q}})$	-0.0075	-0.0357	-0.7418	1.3747	0.3784	0.5854	0.0283
	-log(VRP)	0.2901	0.2888	-0.1411	0.7128	0.1275	-0.0110	0.0308
	$\log(E^{\mathbb{P}})$	-0.0824	-0.1134	-0.9537	1.1745	0.4095	0.4762	-0.2952
Germany	$\log(E^{\mathbb{Q}})$	0.1794	0.1216	-0.4946	1.4717	0.3573	0.7574	0.1864
	-log(VRP)	0.2619	0.2619	-0.1988	0.7657	0.1408	0.0686	0.1154
	$\log(E^{\mathbb{P}})$	-0.1472	-0.1653	-0.9626	1.0540	0.3796	0.3643	-0.3734
France	$\log(E^{\mathbb{Q}})$	0.1436	0.1182	-0.7262	1.4074	0.3480	0.5546	0.1234
	-log(VRP)	0.2908	0.2908	-0.1935	0.7628	0.1347	-0.0329	0.1677
	$\log(E^{\mathbb{P}})$	-0.2343	-0.2858	-1.1188	1.0214	0.4189	0.5788	-0.1767
Netherlands	$\log(E^{\mathbb{Q}})$	0.1216	0.0589	-1.1973	1.4472	0.3964	0.7180	0.0491
	-log(VRP)	0.3560	0.3533	-0.6894	0.9423	0.1426	-0.0386	0.7912
	$\log(E^{\mathbb{P}})$	-0.3700	-0.4713	-1.1576	0.9693	0.3929	0.8324	0.2339
Switzerland	$\log(E^{\mathbb{Q}})$	-0.0177	-0.1026	-0.8525	1.5277	0.3998	0.9324	0.6924
	-log(VRP)	0.3523	0.3442	-0.1527	1.0819	0.1625	0.3442	0.5870
	$\log(E^{\mathbb{P}})$	-0.2666	-0.2762	-1.1246	0.9477	0.3082	0.2474	0.4608
Japan	$\log(E^{\mathbb{Q}})$	0.2644	0.2554	0.5059	1.5658	0.2945	0.8320	1.7596
	-log(VRP)	0.5311	0.5240	-0.3227	1.3186	0.1808	0.1968	0.2401

Table 2: Risk aversion spillovers from U.S. to other markets
Generalized Forecast Error Variance Distributions are given for responding countries for each of the five periods.
Period 1: Dot-com bubble burst and 9/11 attacks.
Period 2: Relatively stable period.
Period 3: Subprime crisis and Lehman Brothers bankruptcy.
Period 4: European sovereign debt crisis.
Period 5: Relatively stable period.

	Period 1	Period 2	Period 3	Period 4	Period 5
U.K. (FTSE)	0.1067	0.0430	0.1287	0.1204	0.1617
Germany (DAX)	0.0698	0.0515	0.1472	0.1285	0.1120
France (CAC)	0.0500	0.0394	0.1356	0.0863	0.1029
Netherlands (AEX)	0.0472	0.0386	0.1424	0.0952	0.0931
Switzerland (SMI)	0.0198	0.0158	0.0624	0.0748	0.0818
Japan (NIKKEI)	0.0959	0.0276	0.0351	0.0356	0.0554

Table 3: Generalized Forecast Error Variance Distributions due to own shocks

	Period 1	Period 2	Period 3	Period 4	Period 5
U.K. (FTSE)	0.3919	0.4163	0.2695	0.3139	0.4171
Germany (DAX)	0.4391	0.3902	0.3118	0.2916	0.3578
France (CAC)	0.4659	0.3407	0.2752	0.3092	0.2846
Netherlands (AEX)	0.4908	0.4617	0.3378	0.2908	0.3498
Switzerland (SMI)	0.6786	0.6190	0.5002	0.4901	0.6273
Japan (NIKKEI)	0.7916	0.9162	0.7077	0.8903	0.9029