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Keywords: Risk-return relation, Realized GARCH, Volatility feedback, Risk premium

JEL: C13, C22, C51

Revisiting the Risk-return Relation in the Chinese Stock Market: Decomposition of Risk Premium and Volatility Feedback Effect*

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Abstract

The empirical results of the risk-return relationship are mixed for both mature and merging markets. In this paper, we develop a new volatility model to revisit the risk-return relation of the aggregate stock market index by extending the Realized GARCH model of Hansen et al. (2012) with the Wang and Yang (2013) framework, in which the overall risk-return relation is decomposed into a risk premium and a volatility feedback effect. An empirical analysis of three major Chinese stock indices reveals positive risk premium and negative volatility feedback effect, and those findings are stable across different markets and sub-samples. However, their relative magnitudes differ between markets and varies through time.

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1 Introduction

The relation between risk and return has been a central field in finance since the seminal paper by Sharpe (1964). Traditional asset pricing theory postulates a positive relation between return and volatility; namely, high risks lead to high returns. For instance, Merton (1980) argues that an asset's conditional expected (excess) return is positively related to its conditional variance.

However, the empirical results of the risk-return relation vary heavily. Several studies support a positive relationship between excess returns and conditional variance (French et al. (1987), Campbell and Hentschel (1992), Ghysels et al. (2005), Guo and Whitelaw (2006), Bali and Peng (2006), Ludvigson and Ng (2007), Jiang and Lee (2014), etc.). Another group of papers finds a negative relation between the two (Nelson (1991), Glosten et al. (1993), Jensen and Lunde (2001), etc.). Campbell (1987), Chan et al. (1992), Whitelaw (2000), Müller et al. (2011) and Kinnunen (2014) fail to find any significant relation.

The literature typically focuses on mature markets, such as those in the US or Europe. Harvey (2001) argues that emerging markets typically exhibit high expected returns and high volatility. Thus, risk-return relations in such markets may display different patterns from those in mature markets. Theodossiou and Lee (1995) and Santis and İmrohoroglu (1997) find no relation between conditional volatility and expected returns in some Asian countries. Jiranyakul (2011) and Li et al. (2013) find a positive risk-return relationship. Darrat et al. (2011) highlights the sensitivity of the risk-return relations to different model specifications and possible breaks through financial crisis.

In the Chinese stock market, the results are also inconclusive. Chen et al. (2003) and Chen (2013) support that higher volatility results in higher returns. Zhang et al. (2000) and Wang (2011) confirm a negative relationship. Several papers such as Liu and Chang (2002) and Wang and Zhuo (2009) find no significant relationship between the two. This inconclusiveness is also reflected in 1) different sample periods with different results (e.g., Chen and Huang (2002) report that the Shenzhen composite index revealed a positive risk-return relationship from 1997 to 2000 while a larger sample from 1993 to 2001 failed to detect significant results); 2) different models that deliver different results (e.g., Wang (2011) find that the significant results depend on whether the stochastic volatility model is used); 3) different volatility measures that yield different results (e.g., Zuo and Liu (2011) show that continuous volatility components have a positive relation with returns while jump components have a negative relation); and 4) different markets with different results (e.g., Chen (2015) finds that the risk-return relationship is generally positive for the Shenzhen stock market and negative for the Shanghai stock market).

One explanation for these mixed results is the volatility feedback hypothesis introduced by French et al. (1987) and Campbell and Hentschel (1992), in which a higher volatility in the current period induces a higher volatility expectation in the future, a higher expected return and a higher discount rate. The higher expected return is an implication of the traditional equity risk premium. However, a higher discount rate means a lower present value of future cash flow and, as a result, a downside movement in the current stock price. Unlike the equity risk premium, volatility feedback affects the current rather than the next period's expected stock prices. Figure 1 illustrates the mechanism of the two effects. At the end of day $t-1$, a representative investor expects the level of volatility of day t based on his current market information set. Then, he requires some compensation for risk based on the expected volatility (expected risk) of day t. Thus, higher volatility corresponds to lower current price and higher expected returns. This is the risk premium part. During the opening hours on day t. various news and noises arrive at the market and cause the price to fluctuate. If the actual volatility during the opening hours is unexpectedly higher than the investor's expected volatility, he requires a higher expected return in the future, which then causes the contemporary stock price to fall accordingly. This is known as the volatility feedback effect.

[Insert Figure 1 here]

The inconclusive empirical results might be caused by the fact that most of them ignore volatility feedback and regard the overall effect of return over conditional volatility as the sole effect of the equity risk premium. Campbell and Hentschel (1992), Guo and Whitelaw (2006) and Yang (2011) all emphasize the importance of the volatility feedback effect in testing the risk-return relation.

From a technical perspective, the traditional GARCH model does not provide a good platform for volatility modeling. The volatility information is included in the model through the squared return (or absolute return), which is noisy and inefficient (see Andersen and Bollerslev (1998), etc.). The estimated parameters tend to put extreme weight on the past conditional volatility, with little weight on the new shock. It is hard for a GARCH model to track fast-changing volatility dynamics (see Hansen et al. (2012), etc.). Andersen et al. (2003) and other recent literature suggests that realized measures constructed from high frequency data out-preform GARCH models in most aspects of volatility modeling. Bali and Peng (2006) highlight the valuable information of high-frequency data in finding consistent results for the risk-return relation. Thus, it is important to test the risk-return relation using information from realized measures.

Based on the two points mentioned above, this paper models the volatility feedback effect with information from realized measures to better investigate the risk-return relation. The volatility feedback effect is modeled through the framework proposed by Wang and Yang (2013), with a volatility shock added to the traditional GARCH-in-mean model. The conditional volatility in the next period can then be calculated using current information, and then related to the equity risk premium. The newly added unexpected volatility shock shifts the current stock return and helps to identify the volatility feedback effect. Moreover, we also consider the well-known leverage effect (e.g., Nelson (1991), etc.) because it also states the negative relationship between return and volatility. Given that the feedback effect is modeled under a GARCH framework, we seek a GARCH-type model with realized measures and leverage effect as a platform for this paper. We use the Realized GARCH model (Hansen et al. (2012) and Hansen and Huang (2015)) to model the volatility dynamics because it is a simple but complete model for returns and realized measures. Following Wang and Yang (2013), a volatility shock is also added to the current model and the leverage effect is modeled through a Gaussian Copula function for greater flexibility. Given that the aggregate of returns follows a normal log-normal (NLN) distribution, we call this new model the Realized GARCH-NLN.

With the help of this new model, an empirical investigation of the risk-return relation is performed on three major Chinese stock indices: the HuShen 300 Index, the Shanghai Composite Price Index and the Shenzhen Component Price Index. There are several notable findings about these indices. First, all of them have significant positive risk premiums and negative volatility feedback effects. The magnitude of the latter is generally small and leads to a significant positive overall risk-return relation. Second, the risk premium required in the Shenzhen stock market is generally larger than that for the Shanghai stock market. This may be explained by the fact that companies listed in the former tend to have lower market capitalization on average. Third, after the subprime crisis, both markets require higher risk premiums and lower volatility feedbacks than before. The difference is more profound in the Shenzhen stock market. Finally, the Realized GARCH-NLN model provides better consistency in the significance of related effects than the traditional GARCH/EGARCH model with no volatility feedback structures. This highlights the efficiency gain provided by the realized measures in the context of risk-return relation assessment.

The remainder of this paper is organized as follows. Section 2 introduces the Realized GARCH-NLN model and its estimation method. Section 3 provides the empirical results and Section 4 concludes the paper.

2 Econometric Methodology

2.1 Model Specification

The GARCH-in-mean (GARCH-M) model proposed by Engle et al. (1987) has been widely used to study the relation between return and conditional variance. In this paper, we investigate the risk-return relation at the daily level based on a Realized GARCH model. Hansen et al. (2012) propose using realized volatility to measure the conditional variance, which is similar to the GARCH-X model. Their model can be written as

$$r_t = \sqrt{h_t} z_t \qquad z_t \sim N(0,1)$$
$$\ln h_t = \omega + b \ln h_{t-1} + a \ln x_{t-1}$$
$$\ln x_t = \psi + \varphi \ln h_t + u_t \qquad u_t \sim N(0, \sigma_u^2)$$

where r_t is the return of an asset at the end of date t and x_t is the realized measures of volatility. The novel specification of their model is the measurement equation, which links the conditional variance to the realized volatility.

To model the risk-return relation, we first consider the mean equation of the Realized GARCH model. The stock price change can be decomposed into two components: the expected price change (risk premium) that investors require based on the prior information and the unexpected price change due to unexpected news and noise trading.

Let $\mathcal{F}_t$ be the information set generated by $\{r_t, x_t, r_{t-1}, x_{t-1}, ...\}$. At the end of date $t-1$, investors have an expectation of volatility for date t based on the prior information. Thus, they require a risk premium to compensate their risk.

For a given $\mathcal{F}_{t-1}$, the expected risk premium required by investors at day t can be specified as

$$\mu_t = m_0 + m_1 \sqrt{h_t} \qquad (1)$$

where m_1 is the parameter that measures the magnitude of the risk premium. h_t is the conditional variance of date t, which measures the expected volatility of the representative investor. We assume a set of newly arrived information at date t. The price of an asset changes according to the unexpected news. Let s_t denote the volatility shock, which is independent with $\mathcal{F}_{t-1}$. Wang and Yang (2013) specify the contemporaneous volatility as

$$\sigma_t^2 = \mathrm{var}(r_t \mid \mathcal{F}_{t-1}, s_t) = \theta^2 h_t s_t^2 \qquad (2)$$

where the positive constant θ depends on the mean and variance of s_t^2. For a given $\mathcal{F}_{t-1}$, a large volatility shock s_t leads to a large contemporaneous volatility σ_t^2. Then, they specify the return shock as the standardized score

$$\varepsilon_t = \frac{r_t - \mu_t}{\theta \sqrt{h_t} s_t} \qquad (3)$$

where ε_t implies the direction of the unexpected price change. To capture the possible correlation between ε_t and s_t, the return shock is decomposed as

$$\varepsilon_t = \xi_t + \beta s_t, \quad \xi_t \sim iid\, N(0,1) \qquad (4)$$

where ξ_t is independent of s_t. β is the parameter dictating the correlation between return shock ε_t and volatility shock s_t. Through some mathematical derivation, the return can be expressed as

$$\begin{aligned} r_t &= \mu_t + \beta\eta\sqrt{h_t} + \sqrt{h_t}\nu_t \\ &= m_0 + (m_1 + \beta\eta)\sqrt{h_t} + \sqrt{h_t}\nu_t \end{aligned} \qquad (5)$$

where $\nu_t = -\beta\eta + \beta\theta s_t^2 + \theta s_t \xi_t$. ν_t follows a normal variance mean mixture distribution. Wang and Yang (2013) argue that m_1 represents the risk premium and $\beta\eta$ denotes the volatility feedback effect.

In this paper, we specify that $\ln(s_t^2) \sim N(0,\gamma)$. Hence, the overall shock ν_t follows a normal log-normal mixture distribution $\mathrm{NLN}(\gamma, \beta, -\beta\eta, \theta)$, which is defined by

$$\nu_t \mid \theta^2 s_t^2 \sim iid\, N(-\beta\eta + \beta\theta s_t^2, \theta^2 s_t^2), \quad \ln(\theta^2 s_t^2) \sim iid\, N(\ln(\theta^2), \gamma) \qquad (6)$$

where $\theta = 1/\sqrt{\beta^2 e^{\gamma}(e^{\gamma} - 1) + e^{\gamma/2}}$, $\eta = \theta e^{\gamma/2}$.

To complete the model, we must model the conditional variance. The advantage of Realized GARCH is that it can model conditional variance more accurately and dynamically via the incorporation of realized measures of volatility. However, it is not straightforward to link realized volatility and the conditional variance, as they are generated from different information sets. In the Realized GARCH model, u_t contains both the volatility shock at date t and the sampling error of the realized measure of volatility. To separate the volatility shocks from the sampling error, we specify the measurement equation as

$$\ln x_t = \psi + \varphi \ln \sigma_t^2 + \eta_t \qquad (7)$$

where σ_t^2 is the contemporaneous volatility at date t and η_t denotes the sampling error of realized volatility. Substituting equation 7 with Equation 2, we get

$$\begin{aligned} \ln x_t &= (\psi + \varphi \ln \theta_1^2) + \varphi \ln h_t + (\varphi \ln s_t^2 + \eta_t) \\ &= \phi + \varphi \ln h_t + u_t \end{aligned} \qquad (8)$$

Finally, we can write our model as

$$\begin{aligned} r_t &= m_0 + (m_1 + \beta\eta)\sqrt{h_t} + \sqrt{h_t}\nu_t \\ \ln h_t &= \omega + b \ln h_{t-1} + a \ln x_{t-1} \\ \ln x_t &= \psi + \varphi \ln h_t + u_t \end{aligned}$$

2.2 Estimation

In this section we present the estimation strategy for our model. Although the original Realized GARCH model uses an explicit quadratic function to model leverage effect, it is not directly applicable to our case because we have three random shocks. A much simpler way is to model the distribution for observable shocks (ν_t, u_t). Given that the marginal distribution of ν_t is not Gaussian, it is unlikely that we can model the joint distribution as a bivariate normal distribution. When direct modeling is not applicable, the copula technique is often used to provide joint distribution through marginal distributions. Here, we use the Gaussian copula to link the marginal distributions of ν_t (Normal log-normal) and u_t (Normal). The parameter for this copula function measures the "correlation"[1] of ν_t and u_t. A negative parameter represents the typical leverage effects between return and volatility. Together, the parameters for maximum likelihood estimation are $(m_0, m_1, \omega, a, b, \beta, \gamma, \lambda, \varphi, \sigma_u, \rho)$. For our model, the parameters can be easily estimated using the method of maximum likelihood. We use a two-stage estimation method to estimate our model for its ease of computation. Given the information set $\mathcal{F}_{t-1} = \{r_t, x_t, r_{t-1}, x_{t-1}, \ldots\}$, the joint log-likelihood function can be expressed as

$$\begin{aligned}\log L(\{r,x\}_{t=1}^{n};\theta) &= \sum_{t=1}^{n}\log f(r_t, x_t \mid \mathcal{F}_{t-1}) \\ &= \sum_{t=1}^{n}\log f(r_t \mid \mathcal{F}_{t-1}) + \sum_{t=1}^{n}\log f(x_t \mid r_t, \mathcal{F}_{t-1})\end{aligned}$$

where n is the number of observations.☒

The first-stage estimator of parameters $(m_0, m_1, \omega, a, b, \beta, \gamma, \lambda, \varphi, \sigma_u)$ can be obtained by maximizing the likelihood above. The two-stage estimator of the Gaussian copula parameter ρ can then be computed as

$$\hat{\rho} = \arg\min_{\rho} \sum_{t=1}^{n} \log c(F_{1t}(r_t \mid \mathcal{F}_{t-1}), F_{2t}(x_t \mid r_t, \mathcal{F}_{t-1}); \rho)$$

F_{1t} and F_{2t} are the cumulative density functions of the conditional marginal distributions.

From Equation 6, the distribution of returns is

$$r_t \mid c_2^2 s_t^2 \sim iid\, N(m_0 + (m_1 + \beta c_2 s_t^2)\sqrt{h_t}, h_t c_2^2 s_t^2), \quad \ln(c_2^2 s_t^2) \sim iid\, N(\ln(c_2^2), \gamma)$$

Hence, r_t follows a normal distribution conditional on $c_2^2 s_t^2$, which follows a

[1] It is actually the correlation of the probability inverse transformation of ν_t and u_t.

log-normal distribution. The probability density function can then be evaluated by numerical integration; namely, the Gaussian-Kron method.

The log likelihood function of x_t can be given by

$$\sum_{t=1}^{n} \log f(x_t \mid r_t, \mathcal{F}_{t-1}) = \frac{1}{2}\sum_{t=1}^{n}[\log(2\pi) + \log(\sigma_u^2) + u_t^2 / \sigma_u^2]$$

The log likelihood function of the Gaussian copula can be expressed as

$$\sum_{t=1}^{n} \log c(F_{1t}(r_t \mid \mathcal{F}_{t-1}), F_{2t}(x_t \mid r_t, \mathcal{F}_{t-1}); \rho) = \frac{1}{2}\sum_{t=1}^{n}[-\frac{1}{2}\log\rho - \frac{1}{2}((F_{1t}^{-1})^2 + (F_{2t}^{-1})^2 + 2\rho F_{1t}^{-1}F_{2t}^{-1})]$$

where F_{1t}^{-1} and F_{2t}^{-1} are the inverse cumulative density functions of r_t and x_t, respectively.

3 Data and Empirical Results

3.1 Data

Our empirical results are based on the daily logarithmic returns for three major stock indices: the HS300 Index (HS300), the Shanghai Composite Price Index (SHCI) and the Shenzhen Component Price Index (SZCI). Given that the average market capitalization of the companies listed in the Shanghai stock exchange is larger than those listed in the Shenzhen stock exchange, the SHCI can be viewed as representing large stocks while the SZCI represents relatively small stocks. We use the realized kernel (RK) proposed by Barndorff-Nielsen et al. (2008) as the realized measure because it is robust to market microstructure noise. The stock index data are available from January 5, 2006 to December 31, 2013, delivering 1931 distinct trading days. The data are obtained from the Resset data library.

[Insert Table 1 here]

Table 1 summarizes the basic descriptive statistics for the daily return, RKs and logarithms of daily RKs. Both the returns and the RKs reveal non-zero skewness and excess kurtosis. The average returns and RKs over the sample period for the SZCI are higher than those for the SHCI, which indicates that small stocks have higher returns and volatility on average. The HS300, as an inter-market index, has a modest average return and volatility level.

3.2 Full-sample Results

Table 2 presents the estimation results in the full sample period, where the sandwich formula is used to calculate standard errors.

[Insert Table 2 here]

In accordance with Hansen et al. (2012), we have a much larger coefficient of RK than the coefficient of squared return in the traditional GARCH model. This shows that the RK has more accurate information in updating future volatility. Parameter ϕ is around 1, which reinforces the idea that the last equation in Realized GARCH-type models is the measurement equation. m_1 measures the magnitude of the risk premium, and it is significantly positive for all three indices. This indicates a positive compensation for risk bearing. In contrast, $\beta\eta$, which denotes the volatility feedback effect, is significantly negative for all three indices. The magnitude of the volatility feedback effect is much smaller than the risk premium. As a result, the overall risk-return relation $m_1 + \beta\eta$, defined as the joint relation of the risk premium and the volatility feedback effect, is significantly positive for all three indices. Hence, there is a significantly positive relation between risk and return from 2006 to 2013 for both the Shanghai and the Shenzhen stock markets. Investors generally get high returns when bearing high systematic risk. The correlation parameter for the Gaussian copula is negative and highly significant, revealing a strong leverage effect.

Compared with the SHCI, the SZCI reveals a higher risk premium and a lower volatility feedback effect. The overall positive relation is stronger for the Shenzhen stock market, suggesting that small stocks usually need a higher risk compensation. A notable difference between the SZCI and the SHCI lies in the variance of the log-square volatility shock $\ln(s_t^2)$. Due to the zero mean of $\ln(s_t^2)$, the significantly lower for the SZCI indicates that the volatility shock is relatively lower for small stocks. It might be counter-intuitive at first glance, but it is consistent with the data shown in Table 1. logRK for the SZCI has a higher mean and lower standard deviation. Moreover, small stocks usually have lower (if not zero) dividend yields. A rise in the discount rate has less effect on their prices.

3.3 Mean Equation Specification

For the mean equation, traditional risk-return relation studies use three types of specifications: 1) the square-root of conditional volatility, 2) the conditional volatility itself and 3) the logarithm of conditional volatility. As a robustness check, we examine whether the two remaining specifications alter the results reported in Table 2.

The variance specification is given by

$$r_t = m_0 + (m_1 + \beta\eta)h_t + \sqrt{h_t}\nu_t$$

The log variance specification can be expressed as

$$r_t = m_0 + (m_1 + \beta\eta)\log(h_t) + \sqrt{h_t}\nu_t$$

Table 3 reports the related results. Given that the specification of variance differs from model to model, the magnitude of parameters cannot be directly compared across different models. However, the relative magnitude of the risk premium and the volatility feedback within each specification is in line with Table 2.

3.4 Results for Sub-samples

Studies indicate that the mixed empirical evidence is partially a result of the time varying facts of the risk-return relation.[2] To investigate the possible change in the risk-return relation after the subprime crisis, we divide our data into two sub-sample periods: January 5, 2006 to December 31, 2009 (covering the subprime crisis) and January 4, 2010 to December 31, 2013. The results are presented in Table 1. The significant difference between the two sub-samples indicates a profound structural change after the subprime crisis.

During the first sub-sample, the risk premium parameter m_1 is neither small nor statistically significant. Thus, there is no significant risk premium. It might be a sign of irrationality, as the first sub-sample contains a strong bull and bear market. During the bull market, when all of the stocks move upward, a simple buy and hold strategy can provide enough returns. Thus, investors generally do not care much about the risk premium. During the bear market, when all of the stocks move downward, most investors are inactive (either leaving the market or becoming trapped within it). The market is full of risk with little premium. During the second sub-sample, the risk premium parameter grows significantly larger, indicating significant risk premium requirements, which is a sign of rationality. The volatility feedback effect $\beta\eta$ is significantly negative in both sub-samples. However, the magnitude is much smaller after the crisis. The overall risk-return relation parameters for all three indices are close to 0 in the first period. Then $m_1 + \beta\eta$ increases to about 1.0 and is statistically significant after the crisis. Economically, the results suggest that a one-standard-deviation increase in volatility is associated with roughly 1% increase in the expected return. The risk premium of the SZCI is consistently larger than that of the SHCI in both periods, and the gap widens after the crisis. The overall risk-return relation, $m_1 + \beta\eta$, is negative for the SZCI and positive for the SHCI in the first period. After the crisis, $m_1 + \beta\eta$ for the SZCI changes to positive and surpasses the SHCI.

In short, we find that the overall effect can change its sign in different sub-samples. However, the decomposed risk premium and volatility feedback effect are consistently significant and keep their signs in both sub-samples. This provides additional support for the importance of the volatility feedback effect in

[2] Rossi and Timmermann (2010), Engle et al. (1987) and Yu and Yuan (2011), among others.

understanding the risk-return relation.

3.5 Comparison with (E)GARCH-M Models

We also estimate the risk-return relation parameter using the classical (E)GARCH-M models, which are widely used in related studies. Given that the (E)GARCH-M model cannot take the volatility feedback effect into account, it can only report the overall risk-return relation. A quick review of these two models is as follows: The GARCH-M model is given by

$$r_t = m_0 + m_1\sqrt{h_t} + \sqrt{h_t} z_t$$

$$h_t = \omega + \alpha h_{t-1} z_{t-1}^2 + \beta h_{t-1}$$

The EGARCH-M model is given by

$$r_t = m_0 + m_1\sqrt{h_t} + \sqrt{h_t} z_t$$

$$\log(h_t) = \omega + \alpha(|z_{t-1}| - \frac{2}{\pi}) + \gamma z_{t-1} + \beta \log(h_{t-1})$$

The estimation results of the GARCH-M (EGARCH-M) models are presented in the top (bottom) panel of Table 5. It is clear that the overall risk-return relation parameter m_1 is much smaller than $m_1 + \beta\eta$ of the Realized GARCH-NLN model for all three indices. The results for the Shenzhen stock market are even statistically insignificant. To some extent, this contrast explains the confusion in previous studies using GARCH family models: 1) the model cannot distinguish between the two contradicting effects, leading to inconclusive empirical results, and 2) the GARCH model delivers a relatively poor volatility estimation that leads to inaccurate estimates of m_1. Because the measurement error generally leads to a bias toward zero.

4 Conclusions

In this paper, we propose a new model to revisit risk-return relation of stock markets based on Wang and Yang (2013) and Hansen et al. (2012). The model has two important characters: 1) it can distinguish the risk premium and volatility feedback effect, 2) it includes information from high-frequency data with the help of a Realized GARCH structure.

Based on this new model, empirical results support a significant positive risk premium as well as a significant negative volatility feedback effect over the full-sample period. Although the sign of risk premium is positive over sub-samples, it is not significant in the first sub-sample covering the sub-prime crisis. On the contrary, the volatility feedback effect is not significant in post-crisis sub-sample. As a result, the overall risk-return relation is positive and significant over the full-sample period. During the crisis period, the relation is either weak or inverted. Inter-market comparison shows a higher risk premium and lower volatility feedback effect for small stocks.

Besides the time-varying and inter-market investigation of risk-return relation, several interesting questions are still need further research. First, Baker and Wurgler (2006), Yu and Yuan (2011) documented that market return is positively related to the market's conditional variance in low-sentiment periods but unrelated to variance in high- sentiment periods. Second, Rossi and Timmermann (2010) argued that there is a positive risk-return relation at low and medium levels of volatility, but this relation is inverted at high levels of volatility. An appealing extension of this paper is to check whether our results hold in different period of investor sentiment and volatility levels.

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Table 1: Summary Statistics of Market Return and Realized Kernel.

(a) HS300

Series	Mean	Median	Min	Max	St.Dev	Skewness	Kurtosis	Obs
returns	0.0469	0.1252	-9.6949	8.9310	1.9227	-0.3947	5.5680	1931
RK	2.3976	1.2954	0.1289	32.5390	3.0751	3.5475	21.8056	1931
LogRK	0.3559	0.2588	-2.0489	3.4824	0.9854	0.3418	2.6515	1931

(b) SHCI

Series	Mean	Median	Min	Max	St.Dev	Skewness	Kurtosis	Obs
returns	0.0302	0.1039	-9.2561	9.0345	1.7758	-0.3733	6.2242	1931
RK	2.0233	0.9872	0.1031	32.7373	2.7834	3.9529	27.6489	1931
LogRK	0.1364	-0.0129	-2.2718	3.4885	1.0192	0.4612	2.5396	1931

(c) SZCI

Series	Mean	Median	Min	Max	St.Dev	Skewness	Kurtosis	Obs
returns	0.0524	0.0921	-9.7501	9.1615	2.0038	-0.3579	5.2164	1932
RK	2.9661	1.7248	0.2071	56.9748	3.6236	4.4265	40.5221	1932
LogRK	0.6468	0.5451	-1.5748	4.0426	0.8947	0.4404	2.7402	1932

Note: Returns are reported as percentage changes and RK is reported in the corresponding scale. Obs is the effective sample size. Kurtosis is the original one: it reports 3 for standard normal distribution.

Table 2: Estimation Results for Realized GARCH-NLN model

	HS300		SHCI		SZCI	
	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err
m_1	0.3648	0.1476	0.4643	0.1431	0.5000	0.1626
$\beta\eta$	-0.0639	0.0195	-0.0687	0.0186	-0.0535	0.0227
$m_1+\beta\eta$	0.3009	0.1431	0.3956	0.1398	0.4465	0.1598
ω	-0.1953	0.0303	-0.2128	0.0317	-0.2222	0.0338
a	0.3338	0.0333	0.3298	0.0349	0.3403	0.0357
b	0.5794	0.0371	0.5972	0.0395	0.5713	0.0404
β	-0.0528	0.0164	-0.0562	0.0155	-0.0451	0.0194
γ	0.7720	0.0605	0.8121	0.0599	0.6854	0.0554
λ	0.5634	0.0663	0.6063	0.0704	0.6496	0.0592
φ	1.1561	0.0734	1.1358	0.0680	1.1458	0.0726
σ_u^2	0.2992	0.0132	0.2881	0.0136	0.2626	0.0108
m_0	-0.1266	0.1175	-0.1819	0.098	-0.3224	0.1449
ρ	-0.1449	0.0143	-0.1346	0.0097	-0.1421	0.0258

Robust standard errors are reported, the delta method is applied to the robust standard errors of $\beta\eta$ and $m_1+\beta\eta$.

Table 3: Estimation Results for Different Mean Equation Specifications

	Variance Specification						Log Variance Specification					
	HS300		SHCI		SZCI		HS300		SHCI		SZCI	
	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err
m_1	0.2129	0.0515	0.2386	0.0532	0.2974	0.0833	0.1863	0.0670	0.2509	0.0565	0.3273	0.0821
$\beta\eta$	-0.0650	0.0184	-0.0689	0.0182	-0.0604	0.0229	-0.0631	0.0191	-0.0677	0.0183	-0.0572	0.0214
$m_1+\beta\eta$	0.1479	0.0462	0.1697	0.0466	0.2369	0.0774	0.1232	0.0649	0.1832	0.0518	0.2702	0.0797
ω	-0.1952	0.0299	-0.2092	0.0310	-0.2190	0.0331	-0.1941	0.0301	-0.2158	0.0324	-0.2230	0.0339
a	0.3323	0.0329	0.3260	0.0343	0.3332	0.0351	0.3336	0.0333	0.3334	0.0353	0.3393	0.0360
b	0.5798	0.0366	0.5990	0.0393	0.5707	0.0404	0.5789	0.0373	0.5952	0.0398	0.5680	0.0407
β	-0.0537	0.0155	-0.0565	0.0153	-0.0510	0.0196	-0.0522	0.0161	-0.0554	0.0153	-0.0482	0.0183
γ	0.7742	0.0598	0.8055	0.0588	0.6878	0.0547	0.7672	0.0604	0.8157	0.0607	0.6871	0.0552
λ	0.5653	0.0657	0.6030	0.0701	0.6535	0.0604	0.5603	0.0662	0.6079	0.0703	0.6536	0.0598
φ	1.1600	0.0724	1.1442	0.0676	1.1711	0.0775	1.1579	0.0737	1.1288	0.0667	1.1571	0.0758
σ_u^2	0.2992	0.0132	0.2882	0.0136	0.2628	0.0108	0.2992	0.0132	0.2881	0.0136	0.2627	0.0108
m_0	0.0093	0.0232	-0.0008	0.0002	-0.1254	0.0740	0.1793	0.0486	0.2458	0.0537	0.1593	0.0459
ρ	-0.1444	0.0302	-0.1339	0.0098	-0.1417	0.0733	-0.1369	0.0144	-0.1155	0.0096	-0.1261	0.0143

Robust standard errors are reported, the delta method is applied to the robust standard errors of $\beta\eta$ and $m_1+\beta\eta$.

Table 4: Estimation Results for Realized GARCH-NLN model with two sub-samples

	HS300				SHCI				SZCI			
	2006-2009		2010-2013		2006-2009		2010-2013		2006-2009		2010-2013	
	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err
m_1	0.1676	0.1497	1.0411	0.4263	0.1305	0.1599	0.8632	0.4179	0.1411	0.1885	1.2114	0.4034
$\beta\eta$	-0.1417	0.0345	-0.0124	0.0222	-0.1184	0.0307	-0.0336	0.0250	-0.1562	0.0384	-0.0122	0.0319
$m_1+\beta\eta$	0.0260	0.1430	1.0287	0.4240	0.0122	0.1544	0.8296	0.4159	-0.0151	0.1856	1.1992	0.4047
ω	-0.2001	0.0532	-0.2368	0.0515	-0.2379	0.0546	-0.2416	0.0518	-0.2175	0.0545	-0.2629	0.0528
a	0.4356	0.0527	0.2166	0.0398	0.4379	0.0597	0.2018	0.0368	0.4199	0.0552	0.2713	0.0479
b	0.4769	0.0549	0.6392	0.0580	0.4854	0.0619	0.6661	0.0523	0.4781	0.0616	0.5971	0.0598
β	-0.1204	0.0312	-0.0100	0.0179	-0.0992	0.0268	-0.0272	0.0203	-0.1364	0.0349	-0.0100	0.0261
γ	0.6917	0.0825	0.8628	0.0852	0.7377	0.0788	0.8495	0.0862	0.5821	0.0662	0.8048	0.0867
λ	0.4830	0.0876	0.8755	0.1818	0.5513	0.0809	0.9316	0.2213	0.5746	0.0811	0.8189	0.1231
φ	1.0878	0.0837	1.3565	0.2137	1.0570	0.0853	1.3855	0.2062	1.1014	0.0899	1.1884	0.1762
σ_u^2	0.3455	0.0222	0.2498	0.0155	0.3329	0.0221	0.2392	0.0170	0.3096	0.0186	0.2140	0.0117
m_0	0.3652	0.1308	-0.7716	0.2980	0.3204	0.1322	-0.5228	0.2540	0.4088	0.2080	-1.0000	0.3123
ρ	-0.2054	0.0099	-0.0764	0.0146	-0.1701	0.0163	-0.0999	0.0315	-0.1864	0.0202	-0.0874	0.0088

Robust standard errors are reported, the delta method is applied to the robust standard errors of $\beta\eta$ and $m_1+\beta\eta$.

Table 5: Estimation results for GARCH/EGARCH in mean models

(a) GARCH model

GARCH	m_1	h_0	m_0	ω	α	β
HS300	0.0448	1.0360	-0.0315	0.0288	0.0450	0.9472
	(0.0136)	(0.1635)	(0.0495)	(0.0212)	(0.0054)	(0.0216)
SHCI	0.0325	1.0349	-0.018	0.0211	0.0471	0.9461
	(0.0093)	(0.1234)	(0.0088)	(0.0069)	(0.0058)	(0.0081)
SZCI	0.1248	2.5158	-0.1828	0.0388	0.0478	0.9423
	(0.0922)	(1.8369)	(0.0046)	(0.0162)	(0.0167)	(0.0133)

Robust standard errors are in parenthesis.

(b) EGARCH model

EGARCH	m_1	h_0	m_0	ω	α	γ	β
HS300	0.0948	1.0819	-0.1167	0.0183	0.1140	-0.0064	0.9892
	(0.0235)	(0.3945)	(0.0223)	(0.0143)	(0.0147)	(0.0062)	(0.0225)
SHCI	0.0763	0.9998	-0.0827	0.0148	0.1156	-0.0035	0.9913
	(0.0053)	(0.2034)	(0.0296)	(0.0112)	(0.0171)	(0.0188)	(0.0072)
SZCI	0.1844	2.5058	-0.2965	0.0202	0.1171	-0.0117	0.9878
	(0.2632)	(1.0771)	(0.4620)	(1.0481)	(0.3389)	(0.0626)	(0.7346)

Robust standard errors are in parenthesis.

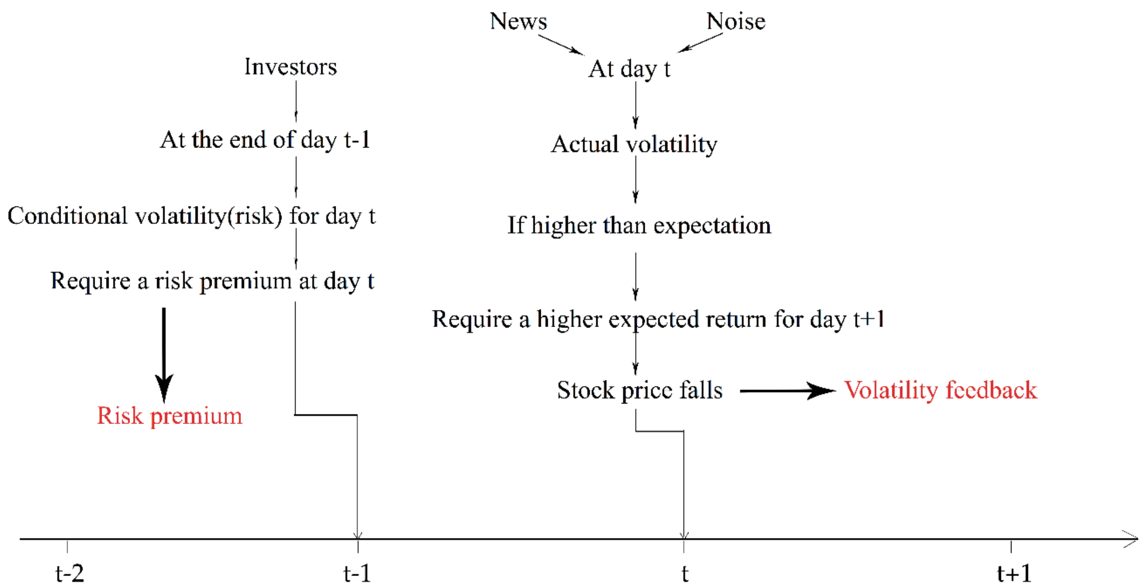

Figure 1: Decomposition of risk premium and volatility feedback effect