The Characteristics of REITs During the Financial Crisis: Evidence from the Stock and Option Markets

by

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Abstract

In this thesis, we examine the characteristics of real estate investment trust (REIT) equity with the sample of Simon Property Group Inc. (SPG) during the financial crisis (from 2006 to 2008). Diavatopoulos, Fodor et al. (2010) study the characteristics of REITs equities and options between 1996 and 2006. We follow their idea and test the influence of the financial crisis on REITs. Contrary to the finding by Diavatopoulos, Fodor et al. (2010), we find that systematic risk drives the risk of both SPG equity and option during the financial crisis. Moreover, we apply an AR(1) model to estimate the conditional idiosyncratic volatility of SPG. For SPG, both implied volatility and historical realized volatility are strong predictors of future realized volatility. Furthermore, the conditional volatility estimated by AR(1) and historical idiosyncratic volatility are also significantly related to future idiosyncratic volatility. Finally, we suggest that none of our SPG volatility measures is a significant factor in predicting SPG returns.

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This thesis is dedicated to my parents who support and encourage me throughout my life.

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CHAPTER I: Introduction and Literature Review

With the rapid development of Real Estate Investment Trusts (REITs) market, considerable financial research has shed light on the property of REITs volatility in last ten years. Most of the literature examines the REITs data before 2008, the initial year of the credit crisis, and find a dominant role of idiosyncratic volatility in total volatility of REITs portfolio. In contrast, this study first analyzes the dynamics of REITs volatility with the sample of Simon Property Groups, Inc. (NYSE: SPG) during the recent credit crisis.

We consider SPG instead of a REITs portfolio as research sample because it is the largest REIT in the United States. Compared to some small cap REITs that are largely illiquid, SPG can provide an effective data series for the whole time period. Furthermore, the correlation of REITs included in REIT portfolio tends to lower the volatility, which reduces the accuracy of testing volatility.

Our first objective is to ascertain if the idiosyncratic risk dominates the SPG return variance during the financial crisis. The risk of REITs can be decomposed into systematic (market based) and idiosyncratic (or firm-specific) volatility. The distinct REITs characteristics tend to benefit from meaningful diversity across the broad geographic regions and segments of the real estate assets market. Some investors believe that this diversity may help lower the market-beta of REITs. Meanwhile, the finance literature supports the pivotal role of idiosyncratic risk in REITs return variance. Observing the firm-specific risk of publicly traded US equity REITs from 1990 to 2005, Ooi, Wang et al. (2009) find that idiosyncratic volatility, on average, equals 78.3% of the total REITs volatility. Additionally, they find that the idiosyncratic risk of REITs is inversely related to REITs market performance, especially idiosyncratic volatility surging severely in market crash. Anderson, Clayton et al. (2005) decompose stock equities into four groups by the capitalization value and test the influence of each groups on REITs returns with multivariable analysis. Their finding suggests that REITs return has been less related to the large capitalization stocks over time, which further supports the decreasing exposure of REITs to market risk. Diavatopoulos, Fodor et al. (2010) employ the market model

(Markowitz 1959) to calculate the idiosyncratic portion of aggregate volatility in REITs. They report that the mean for idiosyncratic volatility constitutes more than 85% of realized volatility from 1996 to 2006.

However, recent studies indicate that the proportion of systematic volatility in REITs may dominate firm-specific volatility, especially during the subprime crisis. Tracking data from four Asian REITs markets during sub-prime crisis, Chiang, Tsai et al. (2013) apply the generalized extreme value (GEV) distribution to disclose that Beta (β), a benchmark explaining the correlated volatility of REITs in relation to the volatility of the volatility of equity market, grows more than two times in the crisis. The decreasing proportion of REITs idiosyncratic volatility can be explained by a high correlation across REITs underlying properties. Chong, Krystalogianni et al. (2011) use a general autoregressive conditional heteroskedasticity-dynamic conditional correlation (GARCH-DCC) framework to reveal that there has been a marked increase in the daily conditional correlation across US REIT sub-sectors since 1990. Their finding confirms a significant proportion of systematic risk in REITs total risk.

Our second objective is to assess the predictive power of SPG ex ante volatility measures. Since Black and Scholes (1973) create an option-pricing model to compute implied volatility, the implied volatility have been widely accepted as the forecast of future return volatility of the underlying security over the remaining life of the relevant option. The financial researchers have produced mixed results about the link between implied and realized volatility. To test the information contained in implied volatility of stock equities, Canina and Figlewski (1993) choose the generalized method of moments (GMM) not only to avoid overlapping data, which may cause serial dependence, but still keep the predictive power of observations in the regression by saving large amounts of data numbers. They find a marked result that implied volatility is insignificantly correlated with future realized volatility. In contrast, Diavatopoulos, Doran et al. (2008) describe that the idiosyncratic part of implied volatility of stock options is a stronger predictor for future firm-specific volatility than the past idiosyncratic volatility or model-forecasted volatility from EGARCH and AR.

Financial researchers recently pay attention to the forecasting ability of REITs implied volatility. Diavatopoulos, Fodor et al. (2010) examine the information included in REITs implied volatility and implied idiosyncratic volatility. Both of these two volatilities are efficient, but biased, predictors of REITs ex-post realized volatility.

Our third objective is to examine the relation between the price of SPG and volatility measures. The influence of systematic or idiosyncratic volatility on equity price is a long-standing debate in financial literatures. In the capital asset pricing model (CAPM), Sharpe (1964) first suggests that equity returns only relate to non-diversified risk. According to modern portfolio theory (Markowitz 1952), the idiosyncratic risk is diversifiable and can be eliminated by the portfolio. This in turn implies that idiosyncratic risk is unimportant in the asset pricing.

However, considerable financial research has paid close attention to the significant relationship between idiosyncratic risk and security return. Merton (1987) disputes that the imperfect nature of actual market can be seen through the high transaction fees, undisclosed information, and regional limitation. Therefore, investors should be compensated for holding non-diversified portfolios, which still contain idiosyncratic risk. Xu and Malkiel (2003) show that the firm-specific risk is positively related to stock return. Using the portfolio's daily return, Goyal and Santa-Clara (2003) find robust evidence of pricing idiosyncratic volatility, but no proof of forecasting power of systematic risk for stock returns. However, Ang, Hodrick et al. (2006) obtain a negative relationship between firm-specific variance and expected returns, when they sort stocks into five portfolios based on the level of one-month lagged idiosyncratic volatility. They report that equities that experience a higher level of idiosyncratic volatility tend to earn lower average returns by the regression of the Fama-French three factors model (FF3).

Although there is a mass of research studying the link between volatility and price on stock market, research about this link on REITs market just emerges in recent years. Referring to the daily return volatility of REITs from 1990 to 2005, Ooi, Wang et al. (2009) first employ the exponential general autoregressive conditional heteroskedasticity (EGARCH)(Nelson 1991) method to calculate the regression between REITs idiosyncratic risk and expected return, which are based on the FF3. In contrast to Sharpe (1964) and Markowitz (1952), they find that there is a positive relation between idiosyncratic volatility and REITs price. Following Ooi, Wang et al. (2009), Imazeki (2012) adds a momentum factor in the FF3 to control for the persistency of REITs returns and extends the data period. Even observing a slight decline of the proportion in idiosyncratic risk in REITs variance, he concludes that the idiosyncratic risk mainly affects REITs price. Diavatopoulos, Fodor et al. (2010) investigate the predictive ability of implied volatility of REITs option and find that neither realized nor implied volatility explains future returns.

Since the volatility calculation is model dependent, it is still difficult to get a consensus about the accuracy of different estimating models. Ooi, Wang et al. (2009) find that REITs volatility is time-varying, thus making it difficult to test the relation between lagged REITs risk and expected return. To explain expected returns, they use an exponential general autoregressive conditional heteroskedasticity (EGARCH) (Nelson 1991) to measure the conditional idiosyncratic volatility in the same period as expected returns. Arguing that the leading-biased conditional volatility estimated by EGARCH tends to overestimate its influence on price, Xu and Malkiel (2003) employ a rolling regression method to estimate volatility. Finally, they show that there is a negligible difference with the GARCH approach. Instead, Diavatopoulos, Fodor et al. (2010) directly regard the implied volatility from REITs option as the ex ante volatility measures.

The remainder of the paper proceeds as follows. In section 2, we delineate the data and present the proportion of idiosyncratic volatility in aggregate volatility. In section 3, we study the predictive power of SPG volatility measures. In section 4, we set up the econometric models and report the relationship between volatility and expected returns of SPG. Then, section 5 concludes.

CHAPTER II: Data and SPG Volatility Characteristics

We build on Diavatopoulos, Fodor et al. (2010)'s research in calculating and analyzing SPG volatility characteristics. We extract daily and monthly return data of SPG and S&P 500, between January 2006 and December 2012, from the Yahoo Finance website. We obtain strike prices, trading volumes, and expiration dates of SPG options from OptionMetrics. To calculate the beta for SPG in a given month, we use daily data for a calendar month rolling window. Expressly, we regress the SPG daily return, $R_{SPG,t}$, on market daily returns within a certain calendar month with the ordinary least squares (OLS) method:

$$R_{SPG,t} = \alpha + \beta_t R_{M,t} + \varepsilon_t \qquad (1)$$

where $R_{SPG,t}$ is SPG daily returns at month t, $R_{M,t}$ is the daily returns of S&P 500 Index at a given month, and β_t is the coefficient .

Before we evaluate the idiosyncratic portion of SPG implied volatility, we need to express a standardized implied volatility for SPG on a given trading day. For SPG options on a given day, there exist contracts with different strike prices and expiration days. We follow the calculation of VIX, which is a standardized degree of the implied volatility of S&P 500 index options over the next 30 days, to create a weighted average of implied volatility (Eq.2) to measure the 30-day implied volatility of daily SPG option. The components of this implied volatility contain call and put SPG options, which will expire in the first and second months. To remove abnormal pricing variances that may occur around expiration, we substitute options that expire in the third contract months for options with less than a week to expiration in the first month. The average implied volatility of SPG near-term option is derived from four selected daily options with two calls and two puts whose strike prices are closest to the price of SPG security, namely at-the-money option. The average implied volatility of SPG next-term option is calculated in the same way. We also remove options with zero trading volume from the data set. We obtain implied volatility, strike price, and volume of trading SPG option from OptionMetrics. The weighted function is as follows:

$$\sigma_{IV,t} = \sqrt{\bar{\sigma}_1^2 \times \left(\frac{\mathrm{T}_2-30}{\mathrm{T}_2-\mathrm{T}_1}\right) + \bar{\sigma}_2^2 \times \left(\frac{30-\mathrm{T}_1}{\mathrm{T}_2-\mathrm{T}_1}\right)} \qquad (2)$$

$$\bar{\sigma}_1 = \frac{\sigma_{c,1} + \sigma_{p,1} + \sigma_{cc,1} + \sigma_{pp,1}}{4}$$

$$\bar{\sigma}_2 = \frac{\sigma_{c,2} + \sigma_{p,2} + \sigma_{cc,2} + \sigma_{pp,2}}{4}$$

where $\bar{\sigma}_1$ is the average implied volatility of near-term option, $\bar{\sigma}_2$ is the average implied volatility of next-term option, $\sigma_{c,1}$ and $\sigma_{cc,1}$ are the implied volatilities of two near-term call options whose strike prices are closest to at-the-money price, $\sigma_{p,1}$ and $\sigma_{pp,1}$ are the implied volatilities of two near-term put options whose strike prices are closest at-the-money price, $\sigma_{c,2}$ and $\sigma_{cc,2}$ are the implied volatilities of two next-term call options whose strike prices are closest to at-the-money price, $\sigma_{p,2}$ and $\sigma_{pp,2}$ are the implied volatilities of two next-term put options whose strike prices are closest to at-the-money price, T_1 is the number of days to expiration for near-term option, and T_2 is the number of days to expiration for next-term option.

After getting the standardized implied volatility, we derive the idiosyncratic portion of implied volatility following Diavatopoulos, Fodor et al. (2010):

$$\sigma_{IV,t}^2 = \beta_t^2 \sigma_{IV_M,t}^2 + \sigma_{IV_{idio},t}^2 \qquad (3)$$

where $\sigma_{IV_M,t}$ is VIX that measures the 30-day expected volatility of the S&P 500 Index at the last day of month t, $\sigma_{IV,t}^2$ is the squared 30-day implied volatility for SPG from Equation (2) at the end day of a given month, β_t^2 is the squared market beta estimated by Equation (1), and $\sigma_{IV_{idio},t}$ is the implied idiosyncratic volatility for SPG. $\sigma_{IV_{idio},t}^2$ is the squared implied idiosyncratic volatility which should be greater or equal to zero . However, almost one quarter of estimated magnitudes of $\sigma_{IV_{idio},t}^2$ have non-positive values. It is a striking result, because it means that for SPG options, the systematic volatility is larger than the implied volatility during the financial crisis.

To find an ex ante risk measure for SPG idiosyncratic volatility, we decide to use conditional idiosyncratic volatility to replace the idiosyncratic portion of implied volatility. There are two common statistical models to forecast idiosyncratic volatility. The first is the EGARCH model proposed by Nelson (1999), which captures the asymmetric change of volatility caused by a stock price rise or drop. Ooi, Wang et al. (2009) first utilize the EGARCH model in the REITs market to calculate conditional idiosyncratic volatility. Following Ooi, Wang et al. (2009), we construct the EGARCH model to derive the conditional idiosyncratic volatility for SPG with the monthly return data, such as:

$$R_{SPG,t} = \alpha + \beta R_{M,t} + \varepsilon_t \qquad \varepsilon_t \sim N(0, \sigma_t^2) \qquad (4)$$

$$ln\, \sigma_t^2 = w + \sum_{l=1}^{p} b_l ln\sigma_{t-l}^2 + \sum_{k=1}^{q} c_k \left\{ \theta \left(\frac{\varepsilon_{t-k}}{\sigma_{t-k}} \right) + \gamma \left[\left| \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \right| - (2/\pi)^{1/2} \right] \right\} \qquad (5)$$

When SPG price increase, γ is equal to zero, while when SPG decrease, γ is less than zero. According to the definition of γ, the term $\gamma \left[\left| \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \right| - (2/\pi)^{1/2} \right]$ will calculate the asymmetric effect by SPG price drop. The conditional idiosyncratic risk of SPG is the square root of conditional variance σ_t^2, which is identified in Equation (5) with a function of the past p-period of residual variance and q-period of asymmetric return effect.

The prerequisite condition of the EGARCH model is that the variance of regression residual, like the variance of ε_t of Equation (4), depends on the previous error terms, namely existing heteroskedasticity of the residual. To determine whether our data pool satisfies this prerequisite, we carry out ARCH LM test (Engle 1982) for ARCH effect detection of Equation (4). The results, shown in Exhibit (1), indicate the absence of ARCH effects, which means that the EGARCH model does not fit our data sample.

The second statistical model to forecast idiosyncratic risk is the autoregressive (AR) model. An AR model representing a type of random process specifies that the dependent variable linearly relates to previous time periods' values, as such:

$$X_t = c + \sum_{i=1}^{p} \beta_i X_{t-i} + \varepsilon_t \qquad (6)$$

where β_i is the parameter of the model, and ε_t is white noise.

To apply an AR model, we evaluate the annualized idiosyncratic volatility ($\sigma_{RV_{idio},t}$) of SPG for each month. We first calculate standard deviation of regression residuals of Equation (1) with SPG daily returns in a given month, and then annualize the daily standard deviation by multiplying the square root of 260, the averaging number of trading days per year, such that,

$$\sigma_{RV_{idio},t} = \sqrt{\frac{260}{N-2}\sum_{n=1}^{N} {\varepsilon_n}^2} \qquad (7)$$

where N represents the number of days in a given month, and ε_n denotes the regression residual on day n in month t.

We also conduct preliminary tests to define the time-series properties of our data sample, which consists of realized idiosyncratic risk, $\sigma_{RV_{idio},t}$, derived by Equation(7), and to determine the feasibility and reliability of an AR model. Exhibit (2) presents our result. The correlogram and Ljung-Box Q-statistic indicate that our data sample fits an AR(1) process. Furthermore, the stationarity is the most essential prerequisite to analyze an AR model. To test stationarity, we resort to the augmented Dickekey-Fuller (ADF) test (Dickey and Fuller, 1979). The result in Exhibit (2) shows that our data series is stationary at the 10 percent significance level, which meets the requirement of conducting an AR model. We construct the AR(1) as follows:

$$\sigma_{RV_{idio},t} = c + \beta\sigma_{RV_{idio},t-1} + \varepsilon_t \qquad (8)$$

where $\sigma_{RV_{idio},t}$ that is calculated by Equation(7) is the idiosyncratic risk at month t.

Appendix describes the figures for our four SPG volatility measures between January 2006 and December 2012. The measures are: (1) $\sigma_{RV,t}$, the SPG realized volatility at month t, which is the annualized standard deviation of SPG daily return within a given month; (2) $\sigma_{IV,t}$, the 30-day implied volatility of SPG option, stemming from Equation (2), on the last day of a given month; (3) $\sigma_{RV_{idio},t}$, the annualized realized idiosyncratic volatility at month t; and (4) $\sigma_{CV_{idio},t}$, the conditional idiosyncratic volatility at a given month, which is forecasted by Equation (8) with the annualized realized idiosyncratic volatility at month t-1.

We present descriptive statistics of these four volatility measures in Exhibit (3). To analyze the influence of financial crisis on the characteristics of SPG volatility measures, we divide our data pool into two parts with September 2008 as the breakpoint, the month of the bankruptcy of Lehman Brothers. Panel A describes the statistics for SPG volatility measures from January 2006 to December 2012. Description for two sub-periods, pre-crisis and financial crisis, is provided in Panel B and C, respectively. Comparing the data about the means of these four volatilities across the two sub-periods, we find that all volatility measures experience a distinct increase during financial crisis. The variances of volatility series reveal that SPG volatility measures are more changeable in financial crisis compared with the pre-crisis period. Specially, the variance of SPG realized volatility in financial crisis is almost five times larger than that in pre-crisis period. The lower kurtosis of SPG volatility in financial crisis further supports that the data has a larger degree of variance. The highly right skewed distributions for all four volatility measures indicate that there exists some extremely large volatility during sample period.

Diavatopoulos, Fodor et al. (2010) also describe three average measures of average realized volatility, average idiosyncratic volatility, and average 30-days standardized implied volatility for REITs equities from 1996 to 2006. They calculate these three volatilities $\sigma_{RV,t}$, $\sigma_{RV_{idio},t}$, and $\sigma_{IV,t}$ in a similar way. Their three measures change smoothly around an average level of 22.5%, 20%, and 35%, respectively. However, our findings differ somewhat from the results by Diavatopoulos, Fodor et al. (2010). Our SPG volatility measures are close to Diavatopoulos, Fodor et al. (2010)'s description for REITs equities in 2006. Nevertheless, from the beginning of 2007, all four SPG volatility measures vary immensely. Especially, after September 2008, the month of Lehman Brothers bankruptcy, all these four volatility measures rapidly escalate to their highest degree, and finally drop back to the level of 2006. $\sigma_{RV,t}$, SPG annualized realized volatility for month t, dramatically soared from a low of 44% in August 2008 to a high of 157% in November 2008, tripling just in three months. Moreover, $\sigma_{RV,t}$ fell from its highest point to 82% in the next quarter, only to rises back to 140% in the following quarter. Afterwards, $\sigma_{RV,t}$ plunged back to 46% in July 2009. SPG 30-days implied volatility, $\sigma_{IV,t}$, experiences a similar trend, but with slightly less fluctuation. Lingxiao Li (2012) suggests that high firm leverage and abuse of short-term debt for REITs companies cause the significant fluctuation of REITs realized volatility during the financial crisis. Overall, the financial crisis alters the characteristic of SPG volatility.

To learn the dominant role in explaining SPG total risk, we examine the proportion of idiosyncratic risk in SPG realized risk. The idiosyncratic risk proportion is defined as the idiosyncratic variance over SPG return variance, as follows:

$$R_{idio}=\frac{\sigma^2_{RV_{idio},t}}{\sigma^2_{RV,t}} \qquad (9)$$

where $\sigma_{RV_{idio},t}$ derived from Equation(7) is SPG annualized idiosyncratic volatility in month t, and $\sigma_{RV,t}$, is annualized SPG realized return volatility in month t.

The results over the study period are reported in Exhibit (4). Theoretically, this proportion should not be more than one. But in our sample, only one month (September 2006) has ratio larger than one. The reason is that market returns explain virtually no variation of the returns to SPG. Moreover, the sample measures in the numerator and denominator in Equation (9) use different degrees of freedom. The ratio, R_{idio} declines from a high level at the start of sample period, reaches a low degree in July 2008, then fluctuates around 40%, and finally soars on Jun 2012. Basically, our finding shows that the idiosyncratic risk largely contributes to SPG total risk in 2006, the year before financial chaos, but during the financial crisis SPG idiosyncratic risk loses its power in driving the behavior of SPG return variance. Specifically, the average percentage of the idiosyncratic risk in SPG total risk is 38% between the year of 2008 and 2009. The low idiosyncratic portion of SPG risk during the financial crisis is markedly different from Diavatopoulos, Fodor et al. (2010), who observe that 87% of the monthly return volatility of the REITs equities is driven by idiosyncratic volatility from 1996 to 2006. Our result further indicates that systematic risk dominates SPG total risk during the financial crisis, which implies that SPG may not be a defensive asset.

To further study the contribution of idiosyncratic risk in the SPG option, we measure idiosyncratic risk proportion as the difference between one and the ratio of the option implied market with derived by implied total risk of SPG:

$$R_{idio\_im} = 1 - \frac{\beta_t^2 \times \sigma_{VIX,t}^2}{\sigma_{IV,t}^2} \qquad (10)$$

where β_t is the market beta calculated by Equation (1) in month t, $\sigma_{VIX,t}$ is the VIX measure on the last day of month t, and $\sigma_{IV,t}^2$ is the 30-days SPG implied volatility derived from Equation (2) on the last day of month t.

Exhibit (5) shows the degree of R_{idio_im}. The result is contrary to the theory that the idiosyncratic risk should not be negative for any equity, or equivalently that market risk is more than 100% of total risk. One possible explanation is the asymmetric REIT-Beta puzzle. The asymmetric REIT-Beta puzzle is defined by Chatrath, Liang and McIntosh (2000) who show that the market-beta of equity REITs tends to be higher when markets are falling, and vice versa. The market-beta of SPG during the sample period is displayed in Exhibit (6). The beta is relatively low before the first quarter of 2007, when the S&P 500 is at a relatively high level. However, when the S&P 500 suddenly plunges at the beginning of 2008, there is a sharp increase in Beta. Basically, the market-beta of SPG during the financial crisis illustrates the asymmetric REIT-Beta relationship. The trend of the idiosyncratic risk from the SPG implied variance is similar to that of the SPG realized variance. The implied idiosyncratic risk averages 16% of SPG implied risk between 2006 and 2012. Diavatopoulos, Fodor et al. (2010) test the idiosyncratic portion of implied volatility for REITs options from 1996 to 2006, and conclude that 95% of implied volatility is implied idiosyncratic volatility. Contrary to their conclusion, the significantly low level of R_{idio_im} in our study suggests a leading role of implied systematic risk in SPG option return risk in the financial crisis.

CHAPTER III: Predictive Power of Volatility Measures

3.1 Implied and Historical Realized Volatilities

With the assumption of an efficient market, the implied volatility of equity should be an unbiased forecast of future equity return volatility over the remaining time of the option contract. To test whether SPG implied volatility subsumes the information in explaining future volatility, we follow the analysis used in Diavatopoulos, Fodor et al. (2010). To avoid overlapping data, which may cause serial dependence, we use annualized data for each month in the sample period and calculate the implied and realized volatility. If the implied volatility is an unbiased predictor for SPG future realized volatility, the intercept coefficient and slope coefficient of implied volatility in function should be equal to 0 and 1, respectively. The function is:

$$\sigma_{RV,t+1} = c + \beta_1 \sigma_{IV,t} + \beta_2 \sigma_{RV,t} + \varepsilon_{t+1} \qquad (11)$$

where $\sigma_{RV,t+1}$is SPG realized volatility in month t+1, estimated as the annualized standard deviation of SPG daily return in month t+1, $\sigma_{IV,t}$ is the 30-day implied volatility of SPG option on the last day of month t, and c and β are estimated coefficients.

The test results for the predictive ability of implied volatility and historical realized volatility in forecasting future SPG realized future volatility appear in Exhibit (7). In Model 1, we only test the predictive ability of SPG implied volatility. The slope coefficient β_1 is significantly positive and the intercept coefficient c is nonzero at the 1% significance level. If, as we state early, implied volatility is regarded as an unbiased expectation of SPG realized volatility under an assumption of efficient markets, we should expect $c = 0$ and $\beta_1 = 1$ in model 1 regression. The t-statistic of 5.28 (not shown) for a test that the slope coefficient β_1 equals to 1 implies that SPG implied volatility is a biased predictor of future realized volatility. This biased estimation suggests that when the implied volatility of SPG option is relatively low, the subsequent SPG realized volatility tends to be higher. Diavatopoulos, Fodor et al. (2010) show that the slope coefficient of implied volatility in a similar model is 0.37, significant at the 1% level.

From Model 2, we see that the magnitude of coefficient of historical volatility is also positive at the 1% significance level, which means that historical volatility also predicts future realized volatility. To test whether implied volatility contains more information of predicting future SPG realized volatility than historical volatility does, we compare the adjusted-R^2 of Model 1 and 2. The adjusted-R^2 of Model 1, 78.93%, is larger than that of Model 2, 73.88%, which indicates that the predictive ability of SPG historical volatility is inferior to that of SPG implied volatility for forecasting future volatility.

Model 3 examines the predictive power of both historical and implied volatility. The coefficient for SPG implied volatility is still significantly more than 1 at the 1% level, while the magnitude of slope coefficient for historical volatility is insignificant at the 10% level. As the coefficient for SPG historical volatility is insignificant, we find that SPG implied volatility includes all the information that historical volatility contains in predicting future volatility. The subtle change of adjusted-R^2 between Model 1 and 3 further supports our finding. To conclude, although both SPG implied and historical volatilities are biased predictors, the implied volatility includes incremental information beyond the historical volatility. Our conclusion is similar to that of Diavatopoulos, Fodor et al. (2010). But their coefficient for implied volatility in a similar Model 1 is just 0.37, notably smaller than our coefficient. The likely explanation is explained by the sample period. Our sample data includes the period of the financial crisis when SPG realized volatility increased resulting in the future volatility being larger than implied volatility.

To see whether there is a structural break around Lehman Brothers bankruptcy, we perform a Chow Breakpoint Test of October 2008 for Model 1. The Chow Test reveals an F-statistic of 7.52 (not shown), implying that the predictive characteristics of SPG implied volatility significantly changes during the financial crisis.

3.2 Conditional and Realized Idiosyncratic Volatilities

Diavatopoulos, Fodor et al. (2007) compare the historical idiosyncratic volatility and conditional idiosyncratic volatility derived from an AR(2) model as predictive measures for future idiosyncratic volatility in the non-REITs equities market. They suggest that historical idiosyncratic volatility is positively and significantly related to future idiosyncratic volatility, but conditional idiosyncratic is an insignificant predictor. We will expand the model by Diavatopoulos, Fodor et al. (2007) in REITs market, and estimate:

$$\sigma_{RV_{idio},t+1} = c + \beta_1 \sigma_{CV_{idio,t+1}} + \beta_2 \sigma_{RV_{idio},t} + \varepsilon_{t+1} \qquad (12)$$

where $\sigma_{RV_{idio},t+1}$ is SPG idiosyncratic volatility in month t+1, calculated using Equation (7), $\sigma_{CV_{idio,t}}$ is conditional idiosyncratic volatility for month t+1 estimated by the AR(1) model (shown as Equation(8)), and c and β are estimated coefficients. Exhibit (8) presents the results.

In Model 1, conditional idiosyncratic volatility is in the model alone and the β_1 is significantly positive at the 1% level. The magnitude of the slope coefficient, 0.79, shows that conditional idiosyncratic volatility is an upward biased predictor of SPG future idiosyncratic volatility. This result is distinct from the result by Diavatopoulos, Fodor et al. (2007) for non-RETIs equities. The significant slope coefficient for SPG historical idiosyncratic volatility in Model 2 suggests that this volatility is linearly related to SPG future idiosyncratic volatility. A comparison of the statistical results of Model 1 to those of Model 2 reveals that the AR(1) forecasts are superior to historical idiosyncratic volatility to predict SPG realized idiosyncratic volatility. The adjusted-R^2 from Model 2 exceeds that from Model 1 by more than 25%, which suggests that SPG historical idiosyncratic volatility contains more information than conditional volatility does. Diavatopoulos, Fodor et al. (2010) also test the predictive power of historical idiosyncratic volatility for REITs equities with a similar model as we use. They find a coefficient β_2 of 0.194 for historical idiosyncratic volatility between 1996 and 2006. Compared with their finding, we conclude that SPG historical idiosyncratic volatility had a larger influence during the financial crisis.

CHAPTER IV: Relation Between The Volatility Measures and Future Returns

Diavatopoulos, Fodor et al. (2010) examine the cross-sectional relationship of expected returns to historical idiosyncratic volatility, realized volatility, and implied volatility on REITs equities from 1996 to 2006. They find that none of these volatilities shows a significant relationship with future returns of REITs. We will test whether this relationship is true during the financial crisis. We measure the estimated coefficients on our four SPG volatility measures to test the respective prices of risk with the following function:

$$R_{SPG,t+1} = c + \beta_1 \sigma_{RV,t} + \beta_2 \sigma_{IV,t} + \beta_3 \sigma_{RV_{idio},t} + \beta_4 \sigma_{CV_{idio,t+1}} + \varepsilon_{t+1} \qquad (13)$$

where c and β are estimated coefficients. The corresponding estimated coefficients for each model are presented in Exhibit (9).

We test whether SPG historical realized volatility predicts returns in Model 1. The ρ-value that is 0.7 for the test statistic of slope coefficient fails to find statistically significant relation between SPG historical realized volatility and returns. We then add SPG implied volatility into the model, and the statistics still show an insignificant relation. We do similar tests for the price of SPG conditional idiosyncratic volatility and historical idiosyncratic volatility in Model 2 and Model 4, respectively. None of the slope coefficients of volatility measures are significantly different from zero. When all four SPG volatility measures are included in Model 5, our SPG volatility measures still are insignificant and do not appear to predict future return. Additionally, negative value of the adjusted-R^2 for each model also suggests that the models contain terms that do not help to predict the response. Our conclusion that none of our volatility measures significantly forecast SPG future return is consistent with that by Diavatopoulos, Fodor et al. (2010).

CHAPTER V: Conclusion

Following the idea by Diavatopoulos, Fodor et al. (2010), we examine the impact of the financial crisis on characteristics of US REITs' volatility from January 2006 to December 2012. The sample of SPG, which is the largest publicly traded retail real estate operating company in America, is used for our research. Diavatopoulos, Fodor et al. (2010) study REIT equities between January 1996 and December 2006 and find that idiosyncratic volatility dominates the total volatility of SPG returns. However, we find that systematic risk drives the risk of both SPG equity and option during the financial crisis. We also suggest that the asymmetric REIT-beta puzzle occurs in the financial crisis. Moreover, we apply an AR(1) model to estimate a forward-looking measure of SPG idiosyncratic volatility in the data period. For SPG, both implied volatility and historical realized volatility are strong predictors of future realized volatility. Furthermore, the conditional volatility estimated by AR(1) and historical idiosyncratic volatility are also significantly related to future idiosyncratic volatility. Although we have a similar conclusion with Diavatopoulos, Fodor et al. (2010), our coefficients of predictive function denote that all of our SPG volatility measures contain more information in estimating future volatility. We also study the significance of our four risk measures in explaining the SPG monthly returns. Nevertheless, the data shows that neither of these four volatility measures is a significant factor in predicting SPG returns, a result that is also concluded by Diavatopoulos, Fodor et al. (2010) for their data sample.

A majority of previous literatures study the characteristic of REITs market before the financial crisis. The striking result of our empirical test is that the financial crisis had a significant influence on the characteristic of SPG volatility, especially around the month of the Lehman Brothers bankruptcy. To investors, our findings may provide useful information in trading REITs during times of financial chaos.

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Exhibit (1)

ARCH Effect Detection of Equation (4)

ARCH LM test

F-statistic	Prob.	F(1,81)
0.089391	0.7657	
Obs*R-squared	Prob.	Chi-Square(1)
0.091497	0.7623	

Correlogram of Squared Residuals

AR order	AC	PAC	Q-Stat	Prob
1	0.033	0.033	0.0958	0.757
2	0.027	0.026	0.1599	0.923
3	-0003	-0.005	0.1609	0.984
4	0.066	0.066	0.5528	0968
5	0.185	0.182	3.6729	0.597
6	-0.020	-0.035	3.7117	0.716
7	0.094	0.090	4.5401	0.716
8	-0.022	-0.028	4.5865	0.801
9	-0.015	-0.043	4.6084	0.867
10	-0.048	-0.077	4.8337	0.902

Notes: This exhibit summarizes the ARCH effect test statistics for the EGARCH model with SPG monthly return data. The reported figures in first table are the statistical result of ARCH LM test. Obs*R-squared is the LM test statistic for the null hypothesis of no ARCH effect. Prob. Chi-Square is the lowest significance level to reject this null hypothesis. In the second table, we present the result of autocorrelations test for squared residual of Equation (4). AC is the autocorrelation coefficients; PAC is the partial autocorrelation coefficients; Q-Stat is the Ljung-Box Q-statistics with 10 lags; and Prob is the lowest significance level at which the autocorrelations hypothesis can be rejected.

Exhibit (2)

Time-series Properties of SPG Idiosyncratic Volatility

Unit root test	t-statistic	Prob
Augmented Dickey-Fuller test statistic	-2.814861	0.0605

	Correlogram			
AR order	AC	PAC	Q-Stat	Prob
1	0.812	0.812	57.318	0.000
2	0.637	-0.063	93.072	0.000
3	0.530	0.094	118.15	0.000
4	0.471	0.077	135.17	0.000
5	0.467	0.157	158.13	0.000
6	0.397	-0.154	172.76	0.000
7	0.276	-0.141	179.92	0.000
8	0.223	0.113	184.64	0.000
9	0.189	-0.019	188.08	0.000
10	0.146	-0.092	190.17	0.000

Notes: this exhibit describes the time-series statistics of SPG monthly idiosyncratic volatility, $\sigma_{RV_{idio},t}$, which is estimated by Equation (7). t-statistic in first part is the the ADF test statistic for the null hypothesis of existing an unit root. Prob is the lowest significance level to reject this null hypothesis. The second part presents the result of autocorrelations test for SPG realized idiosyncratic volatility ($\sigma_{RV_{idio},t}$). AC is the autocorrelation coefficients; PAC is the partial autocorrelation coefficients; Q-Stat is the Ljung-Box Q-statistics with 10 lags; and Prob is the lowest significance level at which the autocorrelations hypothesis can be rejected.

Exhibit (3)

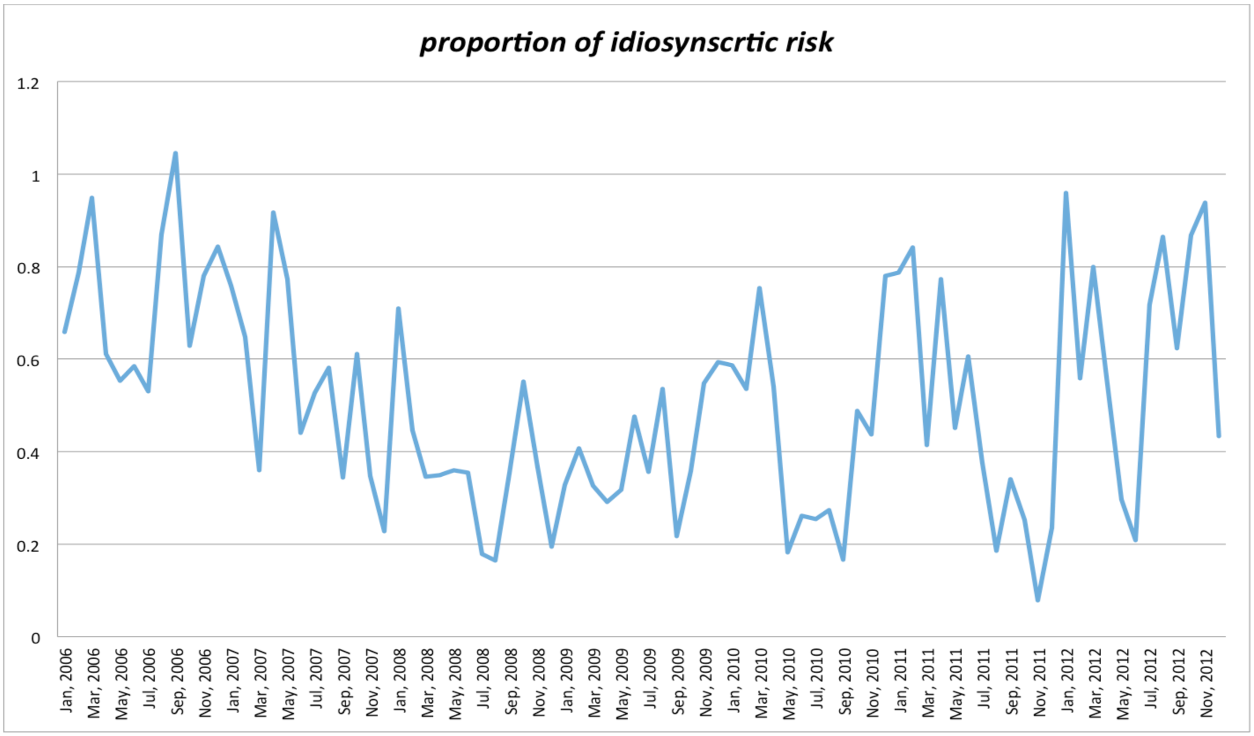
Descriptive Statistics of SPG Volatility Measures

Statistic	$\sigma_{RV,t}$	$\sigma_{IV,t}$	$\sigma_{RV_{idio},t}$	$\sigma_{CV_{idio},t}$
Panel A: Full period: 01/2006-12/2012				
Mean	45.84%	35.19%	29.16%	29.30%
Variance	15.55%	4.36%	5.03%	3.38%
Skewness	2.24	1.99	2.44	2.43
Kurtosis	4.68	3.79	6.24	6.19
Panel B: pre-crisis: 01/2006-09/2008				
Mean	39.22%	29.66%	26.82%	25.90%
Variance	4.97%	1.17%	1.54%	0.50%
Skewness	2.25	0.84	2.50	1.40
Kurtosis	7.60	0.33	8.14	2.72
Panel C: financial crisis: 10/2008-12/2012				
Mean	51.66%	39.18%	31.56%	31.25%
Variance	22.96%	6.13%	7.58%	5.03%
Skewness	1.71	1.53	1.91	1.92
Kurtosis	1.89	1.46	3.03	3.07

Notes: Statistics for the entire sample period (January 2006 to December 2012) are presented in Panel A. Description for two sub-periods, pre-crisis and financial crisis, are provide in Panel B and C, respectively. (1) $\sigma_{RV,t}$, the SPG annualized realized volatility at month t; (2) $\sigma_{IV,t}$, the 30-day implied volatility of SPG option; (3) $\sigma_{RV_{idio},t}$, the annualized realized idiosyncratic volatility at month t; and (4) $\sigma_{CV_{idio},t}$, the conditional idiosyncratic volatility at a given month.

Exhibit (4)

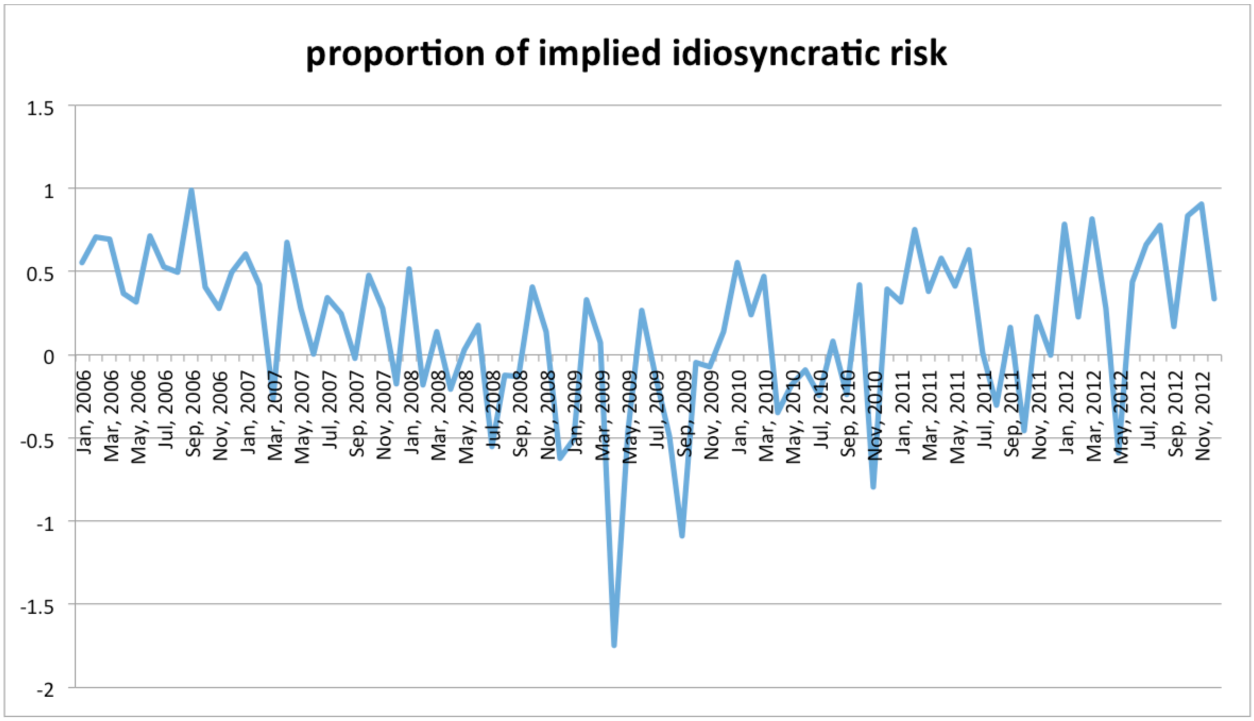
The Proportion of Idiosyncratic Risk in SPG Total Risk



Notes: This exhibit displays the proportion of idiosyncratic risk over total realized risk of SPG from January 2006 to December 2012. The proportion is calculated as R_{idio}=$\sigma^2_{RV_{idio},t}/\sigma^2_{RV,t}$, where $\sigma_{RV_{idio},t}$ is the realized idiosyncratic volatility at month t with market model, and $\sigma_{RV,t}$ is SPG realized volatility at a given month, estimated as the annualized standard deviation of SPG daily returns in month t.

Exhibit (5)

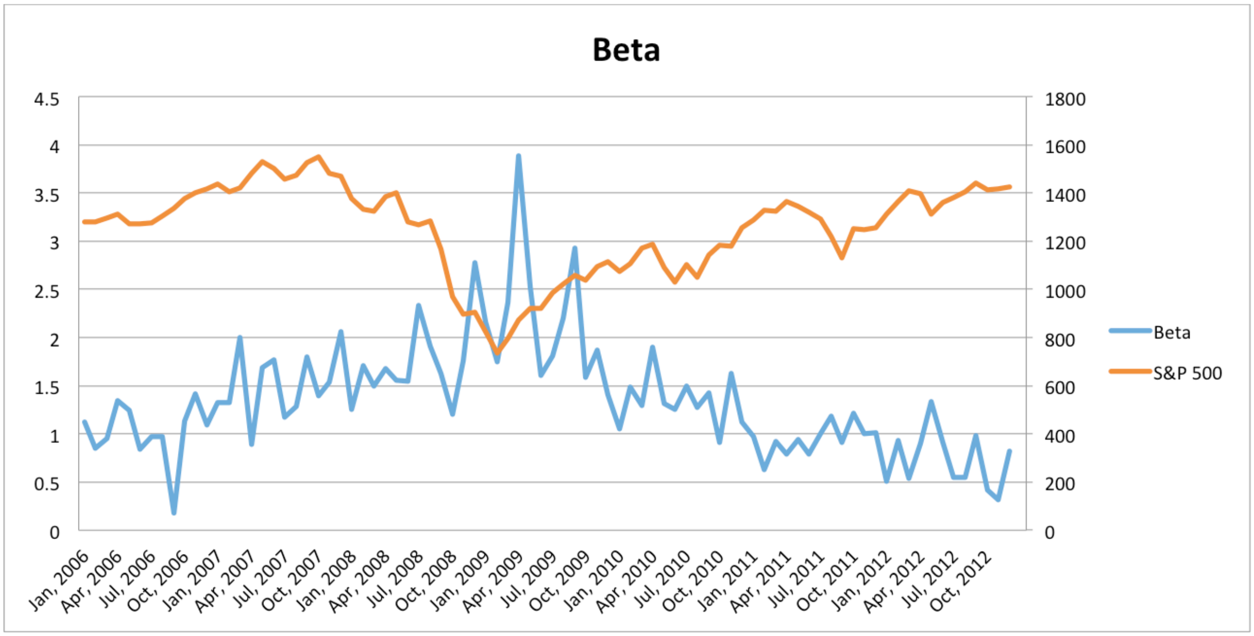
The Proportion of Implied Idiosyncratic Risk in SPG Option Total Risk



Notes: This exhibit displays the proportion of implied idiosyncratic risk over total realized risk of SPG option from January 2006 to December 2012. The proportion is calculated as $R_{idio\_im} = 1 - \frac{\beta_t^2 \times \sigma_{VIX,t}^2}{\sigma_{IV,t}^2}$ where where β_t is the market beta calculated by Equation (1) at month t, $\sigma_{VIX,t}$ is the VIX measure at the last day of month t, and $\sigma_{IV,t}^2$ is the 30-days SPG implied volatility derived from Equation (2) at same day with $\sigma_{VIX,t}$.

Exhibit (6)

The Market-Beta of SPG Equity



Note: the market-beta of SPG equity is calculated by Equation(1), using SPG daily returns within a calendar month.

Exhibit (7)

Forecasting SPG Future Realized Volatility

Model	c	E (β_1)	E (β_2)	R^2(%)	Adj. R^2(%)
1	-0.114523***	1.431282***		79.19	78.93
	(-3.42)	(17.56)			
2	0.062657*		0.862668***	74.20	73.88
	(1.83)		(15.26)		
3	-0.084111**	1.106871***	0.214921	79.72	79.22
	(-2.14)	(4.67)	(1.46)		

Notes: *, **, and *** denotes significance at the 10% level, 5% and 1% level, respectively.
This exhibit presents the regression results of the following equation with data period from January 2006 to December 2012:

$$\sigma_{RV,t+1} = c + \beta_1\sigma_{IV,t} + \beta_2\sigma_{RV,t} + \varepsilon_{t+1}$$

where σ_{RV} is SPG realized volatility, estimated as the annualized standard deviation of SPG daily return within a given month, σ_{IV} is the 30-day implied volatility of SPG option on the last day of month t, and c and β are estimated coefficients. We show the coefficients of each model with t-statistics in parentheses.

Exhibit (8)

Forecasting SPG Future Realized Idiosyncratic Volatility

Model	c	E (β_1)	E (β_2)	R^2(%)	Adj. R^2(%)
1	0.062740*	0.787713***		41.37	40.64
	(1.73)	(7.51)			
2	0.052293**		0.818906***	66.67	66.26
	(2.20)		(12.73)		

Notes: *, **, and *** denotes significance at the 10% level, 5% and 1% level, respectively.
This exhibit presents the regression results of the following equation with data period from January 2006 to December 2012:

$$\sigma_{RV_{idio},t+1} = c + \beta_1 \sigma_{CV_{idio,t+1}} + \beta_2 \sigma_{RV_{idio},t} + \varepsilon_{t+1}$$

where $\sigma_{RV_{idio}}$ is SPG idiosyncratic volatility in month t, which is calculated by the Equation (7), $\sigma_{CV_{idio,t}}$ is conditional idiosyncratic volatility estimated by the AR(1) model in a given month, and c and β are estimated coefficients. We show the coefficients of each model with t-statistics in parentheses.

Exhibit (9)

Forecasting SPG Future Returns

Model	c	E (β_1)	E (β_2)	E (β_3)	E (β_4)	R^2(%)	Adj. R^2(%)
1	0.02020	-0.01240				0.18	-1.05
	(1.2)	(-0.38)					
2	0.02053			-0.2084		0.16	-1.07
	(1.14)			(-0.36)			
3	0.000003	-0.10762	0.16272				
	(0.00)	(-1.13)	(1.06)				
4	0.01276			-0.08680	0.09644	0.97	-1.54
	(0.60)			(-0.87)	(0.79)		
5	-0.00414	-0.12102	0.128956	-0.01262	0.09747	2.15	-2.93
	(-0.12)	(-0.85)	(0.78)	(-0.06)	(0.66)		

Notes: *, **, and *** denotes significance at the 10% level, 5% and 1% level, respectively.
This exhibit presents the regression results of the following equation with data period from January 2006 to December 2012:

$$R_{SPG,t+1} = c + \beta_1 \sigma_{RV,t} + \beta_2 \sigma_{IV,t} + \beta_3 \sigma_{RV_{idio},t} + \beta_4 \sigma_{CV_{idio,t+1}} + \varepsilon_{t+1}$$

where R_{SPG} is SPG monthly return, σ_{RV} is SPG realized volatility, estimated as the annualized standard deviation of SPG daily return within a given month, σ_{IV} is the 30-day implied volatility of SPG option on the last day of month t, $\sigma_{RV_{idio}}$ is SPG idiosyncratic volatility in month t, which is calculated by the Equation (7), $\sigma_{CV_{idio,t}}$ is conditional idiosyncratic volatility estimated by the AR(1) model in a given month, and c and β are estimated coefficients. We show the coefficients of each model with t-statistics in parentheses.

Appendix

Figures for SPG Volatility Measures

Date	$\sigma_{RV,t}$	$\sigma_{IV,t}$	$\sigma_{RV_{idio},t}$	$\sigma_{CV_{idio},t}$
Jan, 2006	18.32%	21.71%	14.87%	N/A
Feb, 2006	16.19%	19.34%	14.36%	17.41%
Mar, 2006	24.81%	19.75%	24.16%	16.99%
Apr, 2006	18.99%	19.62%	14.84%	25.01%
May, 2006	22.99%	24.73%	17.09%	17.38%
Jun, 2006	20.48%	20.60%	15.67%	19.23%
Jul, 2006	19.34%	21.17%	14.09%	18.06%
Aug, 2006	17.13%	16.97%	15.97%	16.76%
Sep, 2006	15.40%	18.71%	15.75%	18.31%
Oct, 2006	12.61%	16.27%	10.00%	18.12%
Nov, 2006	24.03%	18.13%	21.22%	13.42%
Dec, 2006	16.87%	17.87%	15.50%	22.60%
Jan, 2007	19.42%	21.96%	16.92%	17.92%
Feb, 2007	30.89%	26.81%	24.88%	19.08%
Mar, 2007	34.55%	26.08%	20.70%	25.60%
Apr, 2007	20.22%	22.31%	19.38%	22.18%
May, 2007	29.43%	25.95%	25.88%	21.10%
Jun, 2007	31.95%	28.82%	21.20%	26.42%
Jul, 2007	29.10%	33.93%	21.11%	22.59%
Aug, 2007	47.26%	34.49%	36.04%	22.52%
Sep, 2007	34.35%	31.99%	20.12%	34.74%
Oct, 2007	30.46%	35.80%	23.79%	21.71%
Nov, 2007	50.36%	41.32%	29.66%	24.71%
Dec, 2007	41.70%	42.82%	19.91%	29.52%
Jan, 2008	54.14%	47.35%	45.61%	21.53%
Feb, 2008	46.69%	41.63%	31.21%	42.58%
Mar, 2008	53.67%	41.22%	31.53%	30.79%
Apr, 2008	38.30%	31.82%	22.60%	31.05%
May, 2008	27.99%	28.24%	16.77%	23.74%
Jun, 2008	37.84%	40.90%	22.50%	18.96%
Jul, 2008	60.15%	42.92%	25.43%	23.66%
Aug, 2008	43.87%	37.13%	17.76%	26.05%
Sep, 2008	110.52%	60.54%	65.64%	19.78%
Oct, 2008	143.51%	93.69%	106.59%	58.98%
Nov, 2008	156.76%	104.72%	95.00%	92.51%
Dec, 2008	153.64%	87.42%	67.89%	83.02%
Jan, 2009	103.65%	78.91%	59.32%	60.82%
Feb, 2009	81.70%	99.03%	52.16%	53.80%
Mar, 2009	141.60%	108.58%	80.84%	47.95%

Apr, 2009	139.07%	85.46%	75.14%	71.43%
May, 2009	88.21%	60.37%	49.76%	66.76%
Jun, 2009	45.16%	49.52%	31.12%	45.98%
Jul, 2009	46.57%	44.25%	27.79%	30.71%
Aug, 2009	52.25%	46.96%	38.26%	27.99%
Sep, 2009	50.97%	51.92%	23.75%	36.56%
Oct, 2009	42.84%	47.60%	25.65%	24.68%
Nov, 2009	42.76%	44.20%	31.66%	26.23%
Dec, 2009	22.72%	32.83%	17.50%	31.16%
Jan, 2010	26.14%	38.76%	20.02%	19.56%
Feb, 2010	38.74%	33.21%	28.37%	21.62%
Mar, 2010	18.64%	31.40%	16.18%	28.46%
Apr, 2010	41.40%	36.04%	30.43%	18.48%
May, 2010	47.28%	38.88%	20.20%	30.15%
Jun, 2010	37.73%	41.51%	19.30%	21.77%
Jul, 2010	34.75%	31.65%	17.52%	21.03%
Aug, 2010	26.60%	34.61%	13.92%	19.57%
Sep, 2010	25.01%	30.39%	10.21%	16.63%
Oct, 2010	14.29%	25.40%	9.98%	13.59%
Nov, 2010	31.96%	28.58%	21.11%	13.40%
Dec, 2010	19.79%	25.56%	17.49%	22.52%
Jan, 2011	20.63%	22.99%	18.30%	19.55%
Feb, 2011	16.77%	23.10%	15.38%	20.22%
Mar, 2011	19.81%	20.82%	12.76%	17.82%
Apr, 2011	13.81%	18.02%	12.15%	15.68%
May, 2011	13.66%	18.96%	9.17%	15.18%
Jun, 2011	20.57%	21.57%	16.02%	12.74%
Jul, 2011	19.63%	25.40%	12.02%	18.34%
Aug, 2011	61.96%	32.78%	26.67%	15.07%
Sep, 2011	32.49%	42.71%	18.94%	27.07%
Oct, 2011	41.67%	30.19%	20.94%	20.74%
Nov, 2011	33.01%	31.86%	9.21%	22.38%
Dec, 2011	21.83%	23.77%	10.59%	12.77%
Jan, 2012	14.61%	21.07%	14.31%	13.90%
Feb, 2012	11.73%	19.56%	8.76%	16.95%
Mar, 2012	12.84%	19.20%	11.48%	12.41%
Apr, 2012	19.34%	18.23%	14.28%	14.63%
May, 2012	20.15%	25.56%	10.98%	16.93%
Jun, 2012	21.33%	20.89%	9.76%	14.22%
Jul, 2012	13.68%	17.76%	11.59%	13.22%
Aug, 2012	12.04%	20.46%	11.20%	14.72%
Sep, 2012	18.57%	17.02%	14.67%	14.40%
Oct, 2012	10.76%	19.14%	10.03%	17.24%
Nov, 2012	15.03%	16.20%	14.55%	13.44%
Dec, 2012	12.63%	18.09%	8.31%	17.15%

Notes: we report our four SPG volatility measures in this table: (1) $\sigma_{RV,t}$, the SPG annualized realized volatility at month t; (2) $\sigma_{IV,t}$, the 30-day implied volatility of SPG option; (3) $\sigma_{RV_{idio},t}$, the annualized realized idiosyncratic volatility at month t; and (4) $\sigma_{CV_{idio},t}$, the conditional idiosyncratic volatility at a given month.