The Sensitivity of Bank Stock Returns to Real Estate Risks: The Case of the US

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Abstract

The purpose of this paper is to investigate the effect of real estate returns and their volatility on the generation process of US bank stock returns. The approach employs the generalized autoregressive conditionally heteroskedastic in the mean (GARCH-M) model to account for the ARCH effects in daily returns. Most prior studies used OLS and EGARCH to estimate the sensitivity of US bank stocks. However, because ARCH- and GARCH effects are found to be significant, the OLS method may generate inefficient results. In our paper we compare the results generated by OLS and GARCH models. Apart from the traditional volatility equation, we introduce a dummy variable to examine the change in risk before and after the financial crisis. The findings show that real estate returns and their volatility impact US bank stock returns and US bank return volatility directly, and that the impact is more sensitive after the global financial crisis. The occurrence of the global financial crisis shifts US banks' return volatility upward. In addition, most of the individual banks and portfolios exhibit a substantial degree of persistence in shocks. The findings above are important for investors who seek to predict the performance of bank stocks. In summary, our paper adds a real estate return factor into the traditional three-index model and show sthat ARCH and GARCH effects do affect the measures of sensitivity and volatility.

Keywords: Bank stock return, real estate, volatility, GARCH, stocks.

I. Introduction

In recent decades, researchers have shown that the price of stocks can be influenced by many factors including government policies, GDP growth, management of the corporation, etc. Different industries may be affected by different factors. In the banking industry, the interest rate is important for the valuation of common stocks, since banks' profitability is dependent on the interest rate. In addition, the exchange rate is a potential determinant of bank stock returns due to the growing internationalization of the economy (Choi, Elyasiani, and Kopecky, 1992).

In 2008, the world fell into a severe recession due to a banking panic caused by falling real estate prices. Lehman Brothers and Washington Mutual went bankrupt, and Fannie Mae and Freddie Mac[1] were taken over by the US government during the financial crisis (Ivashina and Scharfstein, 2010). Meanwhile, the Dow Jones industrial average index fell from 13,000 to 7,000. The S&P Banks select industry index[2] slumped from around 1,000 to 300, suggesting that banks stock prices reflect the exposure of banks to the poor performance of real estate assets. The current global financial crisis is most likely driven by the deterioration of bank assets like housing and subprime mortgage products. Hence, it would be interesting to investigate that how sensitive US bank stocks are to changes in real estate assets. Since the previous literature has found that real estate investment trusts (REITs) are a major driver of

[1] Lehman Brothers was the fourth largest investment bank in the US, declaring bankruptcy in 2008. Washington Mutual, which was the biggest savings and loan association, collapsed in 2008. Fannie Mae and Freddie Mac were created to expand the secondary market mortgage by securitizing mortgages in the form of mortgage backed securities in the US. In September 2008, both two companies were taken over by the Federal Housing Finance Agency (FHFA) due to financial crisis. (*Source from Wikepeida)*

[2] S&P Banks select industry index is designed to measure the performance of asset management and Custody banks, diversified banks, other diversified financial services, thrift & mortgage finance. The definition was retrieved from http://us.spindices.com/indices/equity/sp-banks-select-industry-index

financial industry risk (Cheong, Olshansky and Zurbruegg 2011), in our paper we will choose the REITs index to describe innovations in the real estate market.

According to previous empirical results, the real estate return should be a relevant factor in terms of explaining bank stock returns and risks (He, Myer and Web 1996). However, He, Myer and Web estimated the sensitivity to real estate using OLS, an estimation method is inefficient in the presence of ARCH and GARCH effects, which are not uncommon in stock market data. Therefore I would like to employ a GARCH (generalized autoregressive conditional heteroskedasticity) model, which can measure the volatility of a time series, to capture the properties of the data.

This method has been used by Elyasiani and Mansur (1998) and Nathan and Vezos (2006) to analyze the response of US bank stock returns to interest rates. However, their models include only one or two risk factors. There is no empirical study examining the joint interaction of interest rates, exchange rates and real estate within a GARCH model. Although there is a large literature examining the link between volatility within certain sectors and the overall market risk, the relationship between real estate return volatility and bank stock return volatility is an area that few researchers have investigated before. In this paper we attempt to fill this gap by examining the sensitivity of US bank stock returns to real estate. In addition, we test whether the volatility of real estate returns affects the bank stock generation process. We also compare the sensitivity to real estate return volatility before and after the global crisis, and investigate whether this change in sensitivity holds for both US regional banks and large money center banks. Finally, we investigate the degree of persistence in shocks for individual banks, a portfolio of regional banks, a portfolio of money center banks, and a portfolio of all the individual banks.

The outline of the paper is as follows. Section II reviews the literature. Section III presents the methodology and section IV the data set used in this paper. The empirical results on the sensitivity of bank stocks to real estate and the impact of real estate return volatility on bank stock risks are discussed in Section V. We conclude in Section VI.

II. Literature Review

Most of the existing studies focus on the sensitivity of bank stock returns to the interest rate and the foreign exchange rate. Stone (1974) was the first to use a two-index model instead of a single-index model to estimate the interest rate impact. The single-index model is

$$\overline{R}_j = a_j + \beta_j \overline{R}_M + \overline{\varepsilon}_j\,, \tag{1}$$

where $\overline{R}_j$ is the return on equity *j*, and $\overline{R}_M$ is the return on a market index (usually equity index). Stone (1974) adds an interest rate index to the single-index model, thereby extending the single-index model into a two-index model:

$$\overline{R}_j = A_j + B_j \overline{R}_E + C_j \overline{R}_D + \overline{e}_j\,, \tag{2}$$

where $\overline{R}_E$ and $\overline{R}_D$ are the return on equity and debt respectively. The coefficients B_j and C_j measure the responsiveness of security *j* to equity and debt market movements. Unexpected interest rate changes have usually been used as the interest index in subsequent studies (Flannery and James 1984).

Prior empirical studies that employ the two-index model present two conflicting results. For example, Lloyd and Shick (1977) analyze a sample of 60 banks covering the period from 1969 to 1972 on a monthly basis and find that there is a weak relationship between the interest rate and bank stock returns. Meanwhile, Lynge (1980) utilizes a short-term and a long-term debt return index separately as $\overline{R}_D$. In his paper, he estimates the model for 57 commercial banks using monthly data for the years from 1969 to 1975, and reports that bank stock returns are more sensitive to the bond interest rate than are common industrial stocks. In addition, the bond interest rate has a negative effect on bank stock returns.

Grammatikos et al. (1986) calculate foreign currency net asset positions and foreign assets and liability duration using data for five foreign currencies from 1975 to 1981 and find that exchange rate surprises have a positive effect on average portfolio returns. However, interest rate surprises have a negative effect on average.

Choi, Elyasiani and Kopecky (1986) add the foreign exchange rate return to the two-index model and applied this three-index model to the 48 largest US commercial banks' monthly returns from 1975 to 1987 using an ARIMA (autoregressive moving average) model. In their paper, they consider the joint impact of the stock market return, foreign exchange rates and interest rates on bank stock returns and find that exchange rate innovations cannot be omitted in investigations of the stock returns of large banks. Through comparison between different portfolios, they find that the returns of money center banks are more significantly related to the exchange rate than those of small regional banks.

In addition to exchange rates, interest rates and stock market factors, real estate is considered to be an important risk factor for bank stock returns in recent research. He, Myer and Webb (1996) introduce a real estate factor into the traditional two index model and use OLS to estimate the coefficients based on a sample of 18 overall bank holding company portfolios in the US They conclude that stock market returns, interest rates and real estate returns all have a significant effect on bank stock returns. Furthermore, they find that weekly data always generates stronger evidence for sensitivity than monthly data, based on their comparison between the results generated by daily and monthly data. This conclusion is also reached by Chamberlain, Howe and Popper (1997), whose paper shows that daily data result in more significant coefficients than weekly or monthly data. Therefore subsequent studies use daily data more than ever before.

With the development of the financial system, banks have served as a mortgage lender and used real estate as collateral more frequently in recent decades. Fluctuations in the real estate market can therefore influence the stability of the financial sector (Goodhart and Hofman, 2008). Because borrowers' risk of default depends on the performance of their collateral, asset prices will directly affect bank capital (Von Peter 2009). The asymmetry of information in the credit market induces banks to lend to risky real estate borrowers at lower rates, because it is very difficult for banks to evaluate the risk of borrowers. When house prices are rising, banks do not always implement sufficient background checks on borrowers. During the 2000-2006 period, the US mortgage market opened to a low income population that had previously been excluded. However, 2000-2006 was a real estate boom period, and transaction prices were inflated. The average price of a home increased from around $110,000 in 2000 to $190,000 in 2006, which is nearly 4.5 times the American average income. Historically, home prices were only 3 times the average income in the US. [3] Hence, low income purchasers had to pay high observed transaction prices around 2006. As long as the price of real estate was falling to their historical level, low income borrowers whohad invested in real estate were not able to find new buyers for their houses and tended to default, which resulted in default rates that are beyond the banks' acceptable level (Ben-David 2009). This worthless housing thus increases the financial distress in the banking system. Furthermore, according to the empirical results of Koetter and Poghosyan (2010), the stability of banks is more affected by real estate return volatility rather than the housing price level.

With the development of financial models, financial derivatives are frequently used as investment instruments.[4] Bank losses show up as mark-to-market losses on mortgage-related securities rather than mortgages.[5] Such losses may be significant and may pass down to bank stock investors very quickly, since the mortgage backed securities are issued in the open market, where prices can be checked by investors immediately. So after the global financial crisis, the relationship between real estate and bank stock return will be even closer.

To estimate the parameters of the three-index model that includes interest

[3] The data sourced from Economist Robert Shiller, Yale University listed by the paper "Why home values may take decades to recover" by Dennis Cauchon, USA Today.
[4] The term "financial derivative" refers to a contract whose value is derived from the performance of underlying market factors, such as market securities or indices, credit etc. (*source from wikipedia*)
[5] Mark-to-market means the accounting act of recording the price or value of a security, portfolio or account to reflect it current market value rather than its book value. The definition retrieved from investopedia.

innovations, exchange rate returns and stock market returns, prior empirical studies employ both OLS and GARCH models. But since all the factors are time series variables, it may not be appropriate to use linear estimation. Song (1984) investigates deposit-institution stock returns with a sample of monthly observations from 1978 to 1987. Tthe first to use a two-factor ARCH model for deposit-institution stock returns, he finds that ARCH models are appropriate for analyzing the bank stock returns. Nathan and Vezos (2006) apply an EGARCH model to a sample of 60 US banks' daily data from 1990 to 2001 with a three index model. The empirical results in their paper show that neither OLS nor EGARCH can estimate the parameters efficiently due to non-linearities in the data. However, EGARCH appears to provide a better fit to the data under the assumption that the error term has a conditional t-distribution.

In addition to research on the sensitivity of stock returns to other returns, there exist a number of studies that investigate the role of industry level volatility in forecasting equity market fluctuations. Volatility is of particular interest to many researchers as it is a way to measure risk. Wang (2010) investigates the behavior of 30 industry-specific volatility measures in the US market using OLS. Wang finds that a portfolio which incorporates the real estate sector is one of the most influential factors affecting other industries' volatility and market volatility.

In another study of the role of volatility, Elyasiani and Mansur (1998) employ the generalized autogressive conditionally heteroskedastic to the mean (GARCH-M) model to investigate the effect of the interest rate and its volatility on the data generating process of bank stock returns. Their sample consists of monthly observations for 56 commercial bank stocks over the period 1970 to 1992. To examine whether the monetary policy strategy in 1972 and 1982 had an effect on bank stock risks and return, they include a dummy variable in their GARCH-M model. The model used for estimation is as follows:

$$ER_{j,t} = \phi_0 + \sum_{i=1}^{n} \phi_i ER_{j,t-i} + \theta \Delta rl_{t-1} + r\log(h_{j,t}) + \varepsilon_{j,t} \qquad (3)$$

$$h_{j.t} = \alpha_0 + d_2 D_2 + d_3 D_3 + \alpha_1 \varepsilon^2{}_{j,t-1} + \beta h_{j,t-1} + \delta CVL_{t-1}$$

$$\varepsilon_{jt} | \Omega_{t-1} \sim N(0, h_{t-1})$$

where $ER_{j,t}$ is the excess return on the *j*th portfolio, Δrl_{t-1} is the change in the ten year treasury composite yield, D_2 and D_3 are dummy variables for shifts in the volatility equation due to the changes in the monetary regime in 1979 and 1982, $h_{j,t}$ is stock return volatility, and CVL_{t-1} is conditional interest rate volatility.

Elyasiani and Mansur find that volatility is a significant factor in their bank stock pricing model. The relationship between risk (volatility) and return is negative and varies in magnitude across different portfolios. Using an OLS approach instead, and a sample consisting of daily UK equity sub-industry indices from 1990 to 2010, Cheong, Olshansky and Zurbruegg (2011) also conclude that risk in the real estate sector has been a powerful driver of finance industry volatility over the past two decades. The work of Wang (2010), and Cheong, Olshansky and Zurbruegg (2011) indicates that there is a strong relationship between real estate sector performance and bank stock risk, while the studies of Elyasiani and Mansur (1998) and Song (1994) provide evidence that it is appropriate to use GARCH and ARCH models to capture the data generating process of bank stock returns.

In general, the existing empirical results show that interest rates, exchange rates, real estate and market factors do have an impact on banks' stock returns. The estimated degree of sensitivity may differ due to differences in the frequency of data, estimation method, banks' investment strategies, etc. According to the aforementioned studies, daily data may generate stronger evidence, so in this study we will use daily data and compare the results of the OLS and GARCH estimation methods. Since banks may have adopted a different loan strategy after the global financial crisis, the degree of sensitivity of individual portfolios may be different pre- and post-crisis. In addition, we will analyze the impact of real estate innovations on volatility (risk) of bank stock returns by adding a dummy variable and real estate return innovation to the volatility equation, so that we can check whether real estate return volatility affects bank stock risks.

III. Methodology

Traditionally, researchers have used a three-index model to estimate the effect of the foreign exchange rates and interest rates on the stock returns of banks. However, the global financial crisis has shown that if the prices of real estate assets are falling dramatically, risks in the real estate industry can be transmitted to the financial industry very quickly, since commercial banks now hold more real estate mortgages than ever before.[6] The deterioration of collateral assets may have a significant impact

[6] The total volume of commercial mortgages held by US banks more than tripled in the last decade (Yuliya Demyanyk and Kent Cherny, 2009).

on default risk and banks' profitability, which influences the banks' stock performance further. To examine the effect of real estate market performance prior to and after the global financial crisis on the banking industry, we add a real estate index to the traditional three-index model, so that the model contains four factors: stock market return, interest rate return, foreign exchange return and real estate return.

In this paper, we will use two basic empirical models to examine the responsiveness of US bank stock returns and their volatility to real estate. The first is an OLS model described in section III.1. Section III.2 describes the GARCH-M model used to test the relationship between the volatility of the real estate market and US bank stock returns and to test whether bank risks and returns change after the financial crisis.

III.1 The OLS model

The equation estimated using OLS is the following:

$$R_{jt} = \beta_{oj} + \beta_{mj} R_{mt} + \beta_{ij} R_{it} + \beta_{Ej} R_{Et} + \beta_{rj} R_{rt} + \varepsilon_{jt}, \qquad (5)$$

where R_{jt} is the daily return on portfolio/bank *j* at time *t*, which is assumed to reflect all the risk factors to portfolio/bank *j*. R_{mt} is the stock market return. For US bank stocks, R_{mt} is the average industrial stock performance, which captures the economy-wide factor. R_{it} represents the unexpected change of risk free interest rates, R_{Et} is the foreign exchange return, and R_{rt} is the real estate return. β_m measures the sensitivity of bank stock returns to the overall stock market; β_{ij} is sensitivity to the interest rate return; β_{rj} is sensitivity to real estate returns; β_{Ejt} is sensitivity to exchange rate returns, and β_{oj} is the intercept term. ε_{jt} is assumed to be an iid white noise error term.

Before estimating equation (5), we will use two ways to test for multicollinearity. One approach is to calculate the correlation between the explanatory variables to examine whether a strong linear relationship exists between the independent variables. However, the simple correlations cannot detect linear relationships that involve more than two variables, so in order to describe the overall linear relationship among the four independent variables we regress each of the variables on the others. If there is no multicollinearity, we will estimate the sensitivity of US banks stock returns to real estate using OLS.

III.2 The GARCH-M model

The work of Engle (1982) suggests that OLS estimation of equation (5) may not be appropriate, because financial time series usually exhibit the property that the current time period's error term is related to the square of the previous innovation (or error term). We apply Engle's ARCH test to determine whether there is an ARCH effect in the sample. The test is based on the following model of the variance of ε_{jt},

$$\sigma^2{}_{jt} = \alpha_0 + \alpha_1 \varepsilon^2{}_{j(t-1)} + ... + \alpha_p \varepsilon^2{}_{j(t-q)} \tag{6}$$

where $\varepsilon_{jt} = \sigma_{jt} z_{jt}$, $z_{jt} \sim iidN(0,1)$. The hypothesis is H_0: $\alpha_0 = \alpha_1 = ... = \alpha_q = 0$. In order to implement the test, a version of equation (6) is estimated using the squared OLS residuals to construct estimates of the variance and explanatory variables of the equation.

In comparison to the Generalized Autoregressive Conditional Heteroscedasiticiy (GARCH) (Bollerslev, 1986) model, the ARCH model can only capture a limited number of lags in the derivation of the conditional variance. A GARCH model can allow more lags to influence the variance without increasing the number of coefficients to be estimated. The standard GARCH (p, q) model is

$$\sigma^2{}_{jt} = \alpha_0 + \alpha_1 \varepsilon_{j(t-1)} + ...+ \alpha_p \varepsilon_{j(t-q)} + \beta_1 \sigma^2{}_{j(t-1)} + ...\beta_1 \sigma^2{}_{j(t-p)} \qquad (7)$$

where $\varepsilon_{jt} = \sigma_{jt} z_{jt}$ and $z_{jt} \sim iidN(0,1)$. If we need to test for the persistence of the risk impact we can test for both an ARCH and a GARCH effect.

Among the variance types of GARCH model, we prefer to use the GARCH-M model. The main difference between the basic GARCH model and the GARCH-M model is that the GARCH-M model adds a heteroskedasticity term into the mean equation, equation (5).

The heteroskedasticity term is an explicit function of the conditional variance of the process. We would like to include the conditional variance of returns as a measure of risk; hence we adopt the GARCH-M model (Engel, Lilien and Robins 1987) as our model. Unlike other GARCH models, the GARCH-M model provides a way to examine whether volatility is significantly influences US banks' stock returns. The GARCH-M model allows us to measure how heavily banks rely on real estate performance in the new financial system. As real estate pricing deteriorates, banks may face higher a default probability, which in turn affects banks' profitability and stock prices. Recognizing the real estate industry risks, banks can impose stricter risk controls in the housing mortgage area and avoid further losses. The GARCH-M model will allow us to investigate both the magnitude and the direction of the effect of real estate.

Firstly, we use the traditional GARCH-M (1,1) process to capture the character of time series. The model can be described as follows:

$$R_{jt} = \beta_{oj} + \beta_{mj}R_{mt} + \beta_{ij}R_{it} + \beta_{Ej}R_{Et} + \beta_{rj}R_{rt} + \beta_{j}\log h_{t} + \varepsilon_{j}, \tag{8}$$

$$\varepsilon_{jt} = w + \alpha_{0} + \alpha_{1}\varepsilon_{j(t-1)} \tag{9}$$

$$h_{t} = w + \varphi_{1}\varepsilon^{2}_{t-1} + \rho_{1}h_{t-1} \tag{10}$$

$$\varepsilon_{jt}\big|\Omega_{t-1} \sim N(0, h_{t-1}) \tag{11}$$

where h_t is the conditional variance of the error term and measures stock return volatility. In equation (8) we use h_t in log form, since Engel et al. (1987) estimate the model with both h_t and $\log h_t$, and find that the model with the log standard deviation produces more efficient results. The choice of a GARCH (1,1) model follows Elyasiani and Mansur (1998). The GARCH-M model in our paper will be estimated using the method of maximum likelihood. The results generated by equations from (8) to (11) will permit us to analyze the sensitivity of US bank stock returns to real estate and the persistence of volatility.

To test whether bank risks and returns change after financial crisis, we include additional variables in the volatility equation:

$$h_{t} = w + \varphi_{1}\varepsilon^{2}_{t-1} + \rho_{1}h_{t-1} + dD + \delta CR_{t-1} \tag{12}$$

where CR is the conditional real estate volatility. In the equation (12), D represents a dummy variable for a shift in volatility due to the global financial crisis. The method used to calculate conditional real estate volatility CR deviates from the traditional financial view that the standard deviation can be used to present volatility. In finance, the standard deviation is a means of measuring the risk associated with price fluctuation of a given asset, which is consistent with our goal of examining REITs investment risk associated with price fluctuation. In their study of the influence of real estate risk on market volatility, Cheong, Olshansky and Zurbruegg (2011) defined a measure of monthly market volatility that is standardized to a 22- day month. In our study, since we use daily return data, we prefer to calculate the standard deviation of daily returns over a one-week period (5 business days):

$$stdev(R_{rit}) = \sqrt{\frac{1}{N-1}\sum_{t=1}^{n}(R_{rit} - \overline{R_{rit}})^2} \tag{13}$$

where N equals 5, which represents the five days of the week; R_{rit} is the real estate return on day t, and $\overline{R_{rit}}$ is the mean of real estate returns for the previous five days.

Because it is a variance, h_t, the conditional variance of error term in the GARCH-M model should be positive. In addition, w, φ_1 and ρ_1 are all positive and $\varphi_1 + \rho_1$ should be less than one. These requirements will be tested in section III.

The four-index model of equations (5) and (8) adds real estate to the traditional three-index model, and has not been tested before. For this reason we compare the four- index and three-index models using the adjusted R^2 and the statistic F to see whether the new factor increases the explanatory power as well.

IV. Data

The multifactor model is estimated using daily data over the period from January 3, 2002 to June 27, 2012. The data on individual bank stock price is obtained from (*yahoo finance*)[7]. The bank stock data cover four US money center banks[8] and three regional commercial US banks (a detailed list is provided in the appendix).[9] The interest rate variable is the daily rate of yield on three month US Treasury bills as published in the Federal Reserve Bulletin; Nathan and Vezos (2006) and He, Myer and Web (1996) employ the same measure for the interest rate innovation in their studies. The exchange rate measure is based on a simple basket of seven major currencies equally weighted. The currency basket includes the British pound, the Euro, the Japanese yen, the China RMB, the Australian dollar and the Canadian dollar. This is similar to exchange rate measure of Nathan and Vezos (2006). The real estate measure is generated from the daily historical price of the Dow Jones Equity all REIT Total from *yahoo finance* as the REITs index, which was used by Cheong. Olshansky and Zurbruegg (2011). The market return is calculated based on the Dow Jones industrial average index.

The returns on market, bank stock, interest and REITs are defined to be the first difference of the log of the original series, that is $R_{jt} = \ln Y_{jt} - \ln Y_{j(t-1)}$, $R_{mt} = \ln Y_t - \ln Y_{(t-1)}$, $R_{it} = \ln I_t - \ln I_{(t-1)}$, $R_{Et} = \ln C_t - \ln C_{(t-1)}$ and $R_{rt} = \ln R_t - \ln R_{(t-1)}$. Further details regarding data sources and the construction of the variances can be found in the appendix.

To investigate differences between the performance of regional banks and money center banks, we classify these seven stocks into two portfolios. One is the money

[7] See the appendix for further details on data sources, including web page address.

[8] Money center banks' borrowing and lending activities are with governments, large corporations and regular banks. These banks are involved in national and international financial systems. (investpedia ,http://www.investopedia.com/terms/m/money-center-banks.asp)

[9] The banks were selected from the list of 60 banks studied by Nathan and Vezos (2006). Only banks for which stock price data were readily available were included in this study.

center portfolio and the other is the regional bank portfolio. The portfolios consist of four money center banks and the three regional banks respectively. The classification of the banks follows the classification of Dow Jones. The return on each portfolio is generated as the sum of holding period capital gains on an equally weighted basis[10].

According to the time-series plots shown in graphs 1 to 7, all the independent variables and the returns on the three portfolios fluctuate more after the financial crisis. The interest rate return, real estate return, exchange rate return and stock market return became more volatile around the middle of 2007 and achieved a peak in volatility in 2008. The three portfolios' stock returns also become more volatile around the middle of 2007, but unlike the independent variables, the time at which they peak is different. In graphs 5 and 6 we can see that both the returns of both the portfolio of all banks and the portfolio of money center banks return to the level of volatility before the crisis, but suddenly reach a peak in volatility in 2011. The portfolio of regional bank stock returns achieves a peak in volatility at the end of 2008 and then decreases gradually.

Table 1 presents some descriptive statistics for the explanatory variances of the model and the three portfolios' stock returns. Table 1 indicate that the stock market return, the foreign currency return, the interest rate innovation and portfolio of regional banks display negative skewness, which means the tail on the left side of the probability density function is longer than the tail on the right side and the bulk of the values lie to the right of the mean. However, the real estate return, the portfolio of all

[10] For more details please refer to note 2 in the appendix

banks and the portfolio of large money center banks stock returns show positive skewness, so that the tail on the right side is longer than the left side. Since under normal distribution the skewness is assumed to be zero, OLS estimation may not suitable for the series. The idea that GARCH model may capture the properties of the time series is probably correct under the four index model.

V. Empirical results

In this section we will discuss the OLS estimates and the GARCH estimates. In section V.1, first we will compare the explanatory power of the four index model of equation (5) and the three index model that excludes the real estate return. Then we will test for multicollinearity, autocorrelation, normality and ARCH effects to determine whether the OLS estimates results are reliable. Lastly, we will discuss the implications of the OLS results and compare them with those of prior studies.

In section V.2, we will first test various hypotheses related to the GARCH specification. We will examine the persistence of shocks to banks and portfolios, how the volatility of real estate affects bank stock returns, and whether the financial crisis has affected the risk and returns of US bank stocks. Finally we will compare the GARCH and OLS estimates of the coefficients.

All the tests are carried out using Eviews 6 and data for seven US banks and three portfolios. Equations (8) and (11) are estimated separately for the pre- and post-financial crisis sub periods for all seven individual banks and all three portfolios.[11]

[11] The financial crisis occurred on August 1, 2007

For equation (12) we do not subdivide the sample; instead, we use the entire sample for 2002 to 2012 to test whether real estate volatility after the financial crisis has a greater impact on bank stock risks than before the crisis.

V.1 OLS estimates

As mentioned above, our OLS estimates are based on equation (5). First, we compare the explanatory power of the four index model of equation (5) and a three index model that excludes the real estate return. Table 2 presents the adjusted R^2 values and the F statistics for a test of overall significance for both models, for each of the seven banks and three portfolios examined, for both the pre-crisis and post-crisis subsamples.

The F statistics for both models show that both have statistically significant explanatory power. The explanatory power of the four index model is higher than that of the traditional three index model, although the differences are small in some cases. The adjusted R^2 value for the four index-model is higher than that of the three-index model both before and after the global financial crisis. For example, the portfolio of all banks prior to the crisis has an adjusted R^2 of 0.408. The adjusted R^2 of the three-index model over the period from 2002-2007 is 0.402, which is a little lower. After the financial crisis, introducing the real estate return variable into the traditional model increases the adjusted R^2 of the portfolio of all banks by 15%. Thus both before and after the financial crisis, the four index model exhibits a stronger explanatory power. Similarly, He and Webb (1996) find that a three index model with the factors real estate returns, market returns and interest rate returns can better explain changes in bank stock returns than a traditional two index model excluding real estate returns.

Before examining the OLS estimates more closely, we will check whether there exists a multicollinearity problem in the data. Multicollinearity occurs when two or more explanatory variables in a multiple regression model are highly linearly related. Although multicollinearity does not reduce the predictive power of the model as a whole, it can make the estimates of the individual coefficients less precise.

There are several ways to detect multicollinearity. The simplest way is to examine the correlations between the explanatory variables. When the value of the pairwise coefficient of correlation between two variables is above 0.8, there is a high correlation between two explanatory variables. In table 3 we can see that only the correlation between the real estate return (LNR) and the market return (LNM) is relatively high at 0.71. That is because we use the Dow Jones industrial average index to represent the market return and use equity REITs to measure the real estate return. REITs are real estate investment trusts whose performance will affect the stock performance of many industries. According to Cheong, Olshansky and Zurbruegg (2011), REITs are a major driver of market risk, since real estate has become one of the main investment instruments in recent decades. Furthermore, Dow Jones puts a relatively high weight on the real estate industry in calculating the industrial average index. Thus, a positive relationship between the market return and real estate return is not surprising.

The simple correlations cannot pick up linear relationships that involve more than two variables, so to examine the overall linear relationship among the four independent variables we regress each of the variable on the others. The resulting four R^2 values are reported in table 4. All four values of R^2 are below 0.8, which implies that there are no strong linear relationships among the four independent variables. Multicollinearity problems do not exist in our data.

Since the four-index model has better explanatory power than the three-index model, the remaining diagnostic tests are applied to the four-index model only. The results of tests for autocorrelation, normality and ARCH effects are presented in table 5.

We use the Breusch-Godfrey test for first-order serial correlation in the residuals. For this LM test statistic, the null hypothesis is that there is no serial correlation. If we use a 10% significance level in carrying out the test, the results shown in table 5 indicate that there is a serious residual autocorrelation problem for Synovus Financial before the crisis, for Webster and Wells Fargo after the crisis, and for the Bank of America, Citigroup, the portfolio of money center banks and the portfolio of all banks both before and after the crisis. Among the above five individual banks, more than half are regional banks. JP Morgan, the Bank of New York and the regional banks portfolio are the only cases for which autocorrelation does not exist either before or after the crisis. This result is similar to that of Nathan and Vezos (2006) that on a percentage basis, residual autocorrelation is less severe for the regional banks.

One of the assumptions of the classical linear regression model is that the errors should follow a normal distribution. Nonnormal errors will cause t and F tests of linear hypotheses about the coefficients to be invalid, especially in small samples. We use the Jarque-Bera test for normality of the residuals, for which the null hypothesis is that the errors are normally distributed. The results in table 5 imply that the errors are nonnormal for all the banks and portfolios.

In addition, we apply an ARCH test to the residuals of the OLS equation. According to equation (6), we let q equal 1 (one lag) and use a simple ARCH(1) model as follows:

$$\sigma^2{}_{jt} = \alpha_0 + \alpha_1 \varepsilon^2{}_{j(t-1)} \tag{14}$$

The null hypothesis is that there is no ARCH effect in the residuals of the OLS equation. As the seventh column of table 5 indicates, all the individual banks and portfolios reject the null hypothesis. A significant ARCH effect is a sign of misspecification. If there is an ARCH effect, the residual is correlated with previous values of residual. Although correlation in the previous process does not cause the OLS estimates to be biased and in consistent, the estimates will be less efficient. In this situation, we will consider other models like GARCH and ARCH models to better capture the dynamics of the process.

Although the diagnostic test results indicate that there are problems with the OLS estimates, we can still compare our four index model to previous studies that have used OLS. Parameter estimates for all the individual banks from 2002 to July 2007 are presented in table 6. There are 1,454 observations before the crisis and 1,281 observations after the crisis. All the 20 regressions are overall significant, since the F-values are greater than the critical value at the 5% level. However, the p-values for the individual coefficients indicate that in some cases we cannot reject the null hypothesis that a coefficient is equal to zero.

First of all, we analyze the currency return impact on stock returns. The first panel of table 6 indicates that the null hypothesis that no foreign exchange rate sensitivity exists ($\beta_{Ej} = \mathbf{0}$) cannot be rejected for any individual bank or portfolio in the period prior to the financial crisis. Prior studies have also found that foreign exchange rate sensitivity is weakest among the money center banks and that the overall sensitivity is not strong (Nathan and Vezos 2006). As for the interest rate sensitivity results, the interest rate innovation sensitivity for all the individual banks and portfolios is also statistically weak before the crisis. Under the OLS approach, foreign currency returns and interest rate innovation have no impact on the US banks return in our pre-crisis sample.

Unlike the foreign currency return and interest rate innovations, the estimates of the coefficient of the market return ($\boldsymbol{\beta_{Mj}}$) have a positive and prominent impact on all the individual banks and the portfolios returns prior to the crisis. Since real estate return is positively correlated with the market return, nearly all the individual banks and portfolios stock returns are sensitive to real estate returns prior to the crisis at the 10% level or less except Citigroup. In terms of magnitude, all the large money center banks have a weaker real estate sensitivity than regional banks except Wells Fargo.

According to the regression results for the period 2007 to 2012 (post-financial crisis), foreign currency and interest sensitivity increased after the crisis. The foreign currency coefficients of JP Morgan, Bank of New York, Wells Fargo, the portfolio of all banks, and the portfolio of regional banks become statistically significant, although no individual banks or portfolios show significant foreign currency sensitivity in the first period sample. This trend is also present in the test results for the coefficients of the real interest innovation factor. Compared with the data before the financial crisis, Citigroup and JP Morgan exhibit strong interest sensitivity. As for the first period sample, all the individual and portfolio stock returns are significantly related to the overall market return at the 1% level, and all the portfolios and individual banks exhibit significant real estate sensitivity as well.

IV.2 GARCH Estimates

In part IV.1 we carried out an ARCH test whose results show that there is an ARCH effect in all the individual banks and portfolios. It is therefore reasonable for us to use a GARCH model to investigate bank stock returns and then to determine their relationship with real estate risk. Following Elyasiani et al. (1998), we pose several hypotheses about the parameter of the GARCH model. The first three hypotheses are related to the volatility equation (10), while hypotheses H4 to H6 are related to equation (12).

Hypothesis H1 is that $\beta_j = 0$, which implies that the volatility of bank stock returns is not a significant factor affecting banks stock returns. Hypothesis H2 is that return volatility is unrelated to time and the return is homoskedistic. In other words, there are no ARCH or GARCH effects, so that $\rho_1 = \varphi_1 = 0$. Hypothesis H3 is that the data exhibit an ARCH effect rather than a GARCH-M effect, so that $\rho_1 = \beta_j = 0$. In this case, the volatility of returns depends on time but the memory is short term. Turning now to the hypotheses about equation (12), hypothesis H4 is that the return generating process follows a GARCH specification, so that $\delta = \beta_j = 0$. In this situation, real estate return volatility has no impact on bank stock returns. Memory is long term. Hypothesis H5 is that real estate volatility has no effect on the bank stock risk or returns or $\delta = 0$. In this case, the conditional real estate volatility variable does not appear in the volatility equation (12). Finally, hypothesis H6 is that the bank stock risk remains the same pre- and post-financial crisis: d=0.

In order to test hypotheses H1 to H3, firstly we estimate equations (8) to (10) to examine whether bank stock volatility is a significant factor in the bank stock return model[12]. The results in table 7 show that the null hypothesis $\beta_j = 0$ cannot be rejected at the 10% level for most of the individual banks and portfolios. The coefficient $\beta_j = 0$ is found to be significant and positive for the portfolio of money center banks prior to the financial crisis; for Citigroup, Bank of America, JP Morgan, Webster, and the portfolio of regional banks after the crisis; and for the portfolio of all individual banks both before and after the financial crisis. Findings in the literature about the coefficient β_j are mixed; Elyasiani and Mansur (1998) find that there is a significant and negative relationship between risk and return, but Baillie and

[12] To do this test in Eviews6, I selected equation estimation with ARCH method, and then selected log(VAR) under ARCH-M, in the meanwhile, I chose GARCH/ARCH model both with 1 orders in the variance and distribution specification options. I used default specification options for the other specifications like restrictor and error.

DeGennaro (1990) find that the parameter is insignificant. Since the sign and magnitude of β_j depends on the investor's utility function or risk preference (Engle 1987), the difference may be due to the sample choices and period covered.

The coefficient β_j is also called the inter-temporal trade-off between risk and return. In our results, β_j is positive and relatively small (ranging from 0.000464 to 0.002795) when hypothesis H1 is rejected. Six of the eight positive coefficients come from the period after the financial crisis. From graph 2 we know that after the financial crisis, the stock market return fluctuated much more violently than before the crisis. Most bank stocks experienced a dramatic slump from the middle of 2007 to the end of 2008, but bank stock prices rebounded when banks recovered from the loss suffered over the financial crisis after 2009. The frequent fluctuations created huge risks for investors, but at the same time there were speculative opportunities in the bank stock market. Investors who withdrew from the stock market due to the financial crisis returned to the stock market. Although the subsequent Euro sovereign debt crisis still made the future of US bank stock uncertain, most investors believed the bank stock prices were undervalued. If so the huge risk in the bank stock market might lead to an overwhelming profit for investors. According to the explanation in Engle (1987), the investors may have been risk-loving. When the risk (volatility) was higher, investors purchased more stocks leading to a positive relationship between risk and returns.

Because the hypothesis H2 ($\rho_1 = \varphi_1 = 0$) involves two coefficients, we need to carry out a Wald test. The Wald test results reported in table 8 indicate that all the individual banks and portfolios (including pre-financial crisis and post-financial crisis) reject the hypothesis $\rho_1 = \varphi_1 = 0$ at 1% significance level, so for these banks and portfolios there are ARCH or GARCH effects in this model.

In equation (9), the ARCH parameter is φ_1 and the GARCH parameter is ρ_1. The magnitude of φ_1 indicates the effect of the last period's shock, while ρ_1 can indicate the effect of the previous period's shock (Elyasiani and Mansur 1998), so the statistical test of ρ_1 can reveal whether the market has longer memory. The intercept term w in equation (10) is the component of the bank stock volatility that is unrelated to time. As indicated in table 7, w is positive and significant. Therefore, there is a term that is independent of time in the volatility equation. For the individual banks and portfolios in which ARCH and GARCH effects exist, the ARCH parameter φ_1 and GARCH parameter ρ_1 are almost all positive, except for the portfolio of money center before the crisis. For most of the individual banks and portfolios the ARCH parameter is much smaller than the GARCH parameter, which implies that volatility is more sensitive to its own lagged value than it is to the new shock in the previous period. However, for the Bank of New York, the portfolio of money center banks and the portfolio of all banks prior to the financial crisis, the short term memory effect is more prominent than the long term memory effect.

The value of φ_1 plus ρ_1 can help us to measure the persistence of volatility. The estimated value of the sum of φ_1 and ρ_1 is usually very close to one. Given the results in table 7, the sum of φ_1 and ρ_1 is bigger than 1 for the portfolio of money center banks and the portfolio of regional banks after the financial crisis, as well as the portfolio of all individual banks in both periods. These results mean the GARCH model is unstable. Except for these three cases, the sum of the other banks' and portfolios' persistence parameters is all smaller than 1 or equal to 1. When the persistence is equal to 1, there is no mean reversion. A low persistence indicates rapid decay and high reversion to mean. Among our samples, only the Bank of New York prior to the financial crisis has relatively low persistence of around 0.69. So after 6 days, only 0.69^6 (10.8%) of the total initial shock persists. For JP Morgan, before the crisis the persistence measure is as high as 0.99, which implies that after 6 days, 94.1% of initial shocks are still persistent. Since nearly all the individual banks and portfolios seemed to have a persistence measure close to 1, we can conclude that these banks and portfolios are not good at absorbing the variation of shocks. In general, bank stocks are greatly affected by shocks.

To test the remaining hypotheses, we need to introduce real estate's volatility and a dummy variable into the volatility equation. In addition, we pool the data prior to and after the financial crisis for each bank and portfolio. Real estate's volatility is represented by the standard deviation of real estate log differences for a rolling period of 5 business days that includes the current day. The post financial crisis period is denoted by D=1, and the period prior to the crisis by D=0.

As the test results represented in table 9 show, H4 ($\delta = \beta_j = 0$) cannot be rejected at 10% the significance level only for Bank of New York.[13] For this bank, then, the

[13] To do this test in Eviews6, I selected equation estimation with ARCH method, and then selected log(VAR) under ARCH-M, in the meanwhile, I chose GARCH/ARCH model both with 1 orders in the variance and distribution specification options. Since I use equation (12) for this test, I put "dum" and "vol" in the variance box to represent the dummy variable and volatility. I used default specification options for the other specifications like restrictor and error.

return generating process does not follow a GARCH-M model, and real estate volatility is not a prominent component in the volatility equation. The other banks and portfolios can satisfy this hypothesis at the same time.

Under H5, the null hypothesis is that real estate volatility has no effect on bank stock risks and returns ($\delta = 0$). Table 10 shows that for the portfolio of regional banks, Wells Fargo and Citigroup, stock return volatility is not sensitive to real estate volatility. Among the individual banks and portfolios whose return volatility is affected by the change of real estate, δ is positive for JP Morgan, the Bank of New York, Webster, and the portfolio of money center banks. This indicates that if real estate returns are more volatile, bank stock returns will be less stable in the following periods. On the other hand, for the remaining two banks and one portfolio δ is negative. For these two banks and one portfolio, more volatile real estate returns imply more stable bank stock returns. This result is similar to the conclusion of Cheong, Olshansky, and Zurbruegg (2011), who suggest that the REIT component of real estate has become the most powerful leader of financial industry volatility. Exposure to the real estate market is different for each bank and portfolio, which is the reason why different banks and portfolios respond to real estate performance differently. Usually the composition of bank capital plays an important role in stabilizing profitability. Some banks or portfolios hold less real estate-related property or investment. Hence, these banks or portfolios suffer less from unexpected changes in real estate returns. In addition, each bank's capability of managing risk is another factor that influences banks' exposure to real estate risk. Some banks have a more advanced risk control system. For example, some banks may hold hedges to cover the risk from the real estate market.

To investigate the potential effect on the banks' volatility of the financial crisis beginning in July 2007, we introduced the dummy variable D. We assume that the effect of the global financial crisis is manifested in the form of a one time effect on the intercept of the volatility equation. Table 10 shows that the asymptotic t test statistic for hypothesis H6 (d=0) is highly significant for all the portfolios and all individual banks except the Bank of New York. Therefore, the volatility generation process is sensitive to the effect of the global financial crisis. In addition, the dummy variable parameters are positive for six banks and three portfolios, which indicate that the banks' stock risk shifted upward after the crisis. In magnitude terms, the regional banks bear more risk from the financial crisis. Compared to the regional banks, money center banks have a better ability to absorb external risks. A potential explanation may be that money center banks have more channels to enter the financial market so they can choose more investment instruments to diversify risks. In addition, money center banks have more capital compared to median and small sized banks. Since real estate risk is reflected by default risk, money center banks with more flexible assets can bear more default risk.

Under GARCH type model the adjusted R^2 is still not good, but the adjusted R^2 is not a good measure of fit for this model. Although the GARCH model of tables cannot solve all the problems of the OLS estimation, we still prefer to rely on these results when we explain the sensitivity of banks stock returns to real estate, since there is strong evidence of ARCH effects.

First of all, we analyze the sensitivity of real estate returns based on the GARCH-M estimates in Table 7. According to the OLS estimates (table 6), real estate returns are not a prominent factor in Citigroup stock return equations prior to the crisis. In the GARCH model, nearly all the individual banks and portfolios are very sensitive to real estate returns. Only Citigroup's stock return prior to the crisis does not respond to changes in real estate returns. This result is consistent with Davis and Zhu's (2009) study of the relationship between real estate and bank performance that concludes that commercial property loans are often the most volatile component of a bank portfolio. Changes in real estate sector performance will affect banks' profitability. Banks' stock prices will reflect profitability as well, so it is easy to understand why the relationship between real estate returns and bank stock returns is positive and significant.

In term of magnitude, as table 7 shows, all the returns of individual banks and portfolios are more easily and positively affected by real estate market performance after the crisis. For example, the coefficient of real estate returns for the portfolio of all individual banks is 0.10 prior to the financial crisis, and the sensitivity increases to 0.43 in the second period (post-financial crisis). Meanwhile, the money center banks are more sensitive to real estate returns before the crisis compared to regional banks. However, post crisis β_{Rj} (the coefficient of the real estate return) is almost the same for money center banks and regional banks at around 0.42, which means a 1% change of real estate return will cause a 0.42% change in banks stock returns. The regional banks are less sensitive to real estate returns due to the composition of assets. According to Davis and Zhu's studies (2009), at the end of 2007, on average commercial real estate loans accounted for 23% of total interest-earning assets, and 46% for small and median sized banks. Most of the regional banks can be seen as small and median sized banks. Although regional banks have a higher real estate to total interest-earning assets ratio, commercial property price movements have a smaller effect on regional banks than on money center banks. That is because the large banks are capable of taking more risks, so they are willing to lend money to a lower income population. When the global financial crisis came, the commercial real estate price dropped dramatically. The lower income population was the first group to default. Hence large banks like money center banks suffered more losses compared with regional banks, which may be one of the reasons why money center banks are more sensitive to changes in real estate returns after the financial crisis.

Apart from real estate returns, the coefficients of the interest rate and the exchange rate in the GARCH-M model are different from those estimated by OLS. According to the results shown in table 6, none of the individual banks and portfolios are sensitive to interest rate innovation before the crisis at 10% significance level, but in the GARCH-M model (refer to table 7) Citigroup, Synovus Financial, the portfolio of all individual banks and the portfolio of money center banks are sensitive to interest innovations, which is more consistent with previous studies. In the OLS estimation, interest rate innovation is a significant factor affecting Citigoup's and JP Morgan's stock returns after the crisis. However, in the GARCH-M model, Citigroup, Bank of New York, the portfolio of money center banks and the portfolio of regional banks' stock returns are affected by interest rate returns.

As in the case of interest rate returns, none of the individual banks and portfolios are sensitive to exchange rate returns under the OLS approach prior to the crisis. However, in the GARCH model, exchange returns become a significant factor in our mean equation for the portfolio of all individual banks and the portfolio of money center banks before the crisis. Compared to the OLS estimates, JP Morgan and the portfolio of money center banks are not sensitive to exchange returns after the crisis in GARCH-M model. Webster is sensitive to exchange returns in the GARCH-M model but non-sensitive to this factor under the OLS approach. Furthermore, the degree of impact of exchange returns on bank stock returns after the crisis is different between in the GARCH and OLS estimates. In general, banks and portfolios are less sensitive to exchange returns under the GARCH approach than under OLS estimation.

Finally we analyze the pooled time series data results in table 8. We can see that the returns of all the individual banks and portfolios are significantly and positively related to real estate returns from 2002 to 2012. In general, the money center banks are influenced by innovations in the real estate sector more easily than regional banks, which is consistent with the traditional idea that money center banks are more willing to take risks.

VI. Conclusion

Investigations of the relationship between the real estate sector and bank stocks have become very important in recent decades, especially since the global financial crisis. Studying bank stock return's responses to real estate changes before and after the crisis is crucial for investors who would like to predict stock prices and design hedging strategies.

Our study extends previous work in the several directions. First, we introduce a real estate return factor into the traditional three index model. Second, we use a GARCH-M model to estimate the sensitivity of bank stock returns to real estate. This approach allows us to test the impact of the volatility of bank stock returns on bank stock risk, although the results show that bank stock return volatility is not a prominent factor in the return equation. In addition, we add real estate return volatility into the volatility equation so that we can estimate how much the real estate return volatility affects the banks risk. Third, we include a dummy variable in the volatility equation, so that we can compare the banks' risks before and after the financial crisis.

According to our findings, real estate returns have a positive and significant impact on bank stock returns. This impact is different prior to and after the financial crisis. In general, banks and portfolios of banks are more sensitive to real estate returns after the crisis. In addition, regional banks are less affected by real estate sector performance than are money center banks. ARCH and GARCH tests indicate that real estate volatility is an important determinant of bank stock return volatility for most individual banks and portfolios except the portfolio of regional banks, Wells Fargo and Citigroup. The relationship between bank stock return volatility and real estate return volatility is uncertain, due to the investment strategy of banks. The money center portfolios' time series data are unstable under the GARCH approach. Most of the selected banks and portfolios show a high degree of persistence, which indicates slow decay and low reversion to mean. The Bank of New York is the only bank that displays a relatively low persistence.

The burst of real estate bubbles has two effects on bank stock returns. On the one hand, the financial crisis increases the banks' risk. Compared to regional banks, money center banks seem to have a better ability to absorb the external risks. On the other hand, the sensitivity of banks' returns to real estate is different before and after the financial crisis. After the crisis, all the individual bank and portfolio stock returns are more easily and positively affected by the performance of real estate market. In general, innovations in the real estate sector have more impact on money center banks than on regional banks, which is consistent with the traditional idea that money center banks are more willing to take risks.

One limitation of our study is that we don't test for the order of our GARCH model. In our test, we use the default order of 1. Hence, we may have failed to find the optimal lag structure for each bank and portfolio. For future research, the optimal order of GARCH and ARCH models can be tested on each bank and portfolio, so that more accurate results may be obtained.

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Data Appendix.

1. The US bank stock price is retrieved from http://finance.yahoo.com/. The individual bank's return is calculated as follows:

$$R_{jt} = \ln Y_{jt} - \ln Y_{j(t-1)}$$

where Y_{jt} is the adjusted closing price of bank j in day t.

2. There are three portfolios in our paper, large money centers portfolio, regional banks portfolio and portfolio of all individual banks. To calculate the portfolio's return we need to assign the same weights for every individual bank in the portfolio so we assume that we have $100 for each individual bank. Then value of the portfolio in day t is the sum of the value of banks contained in that portfolio. Take the regional banks portfolio as an example. In day one the equity price of Bank of New York, Synovus financial and Webster Financial is 10, 20 and 50 separately. Because we have $100 for each stock, then we are able to buy 10 units of Bank of New York, 5 units of Synovus financial and 2 units of Webster. The original value of the three equities is all $100. The value of portfolio in day one is $300. Assume there is no extra investment in the following 10 years, then the value of the individual banks are only affected by the change of the price. If in day 2, the price of Bank of New York, Synovus financial and Webster Financial is 15, 15, 50, then the value of each bank's equity is 150, 75 and 100. The value of regional banks portfolio is the sum of the value of each bank's equity that is $325. The formula to calculate the portfolio return is:

$$R_{it} = \ln Y_{it} - \ln Y_{i(t-1)}$$

where Y_{it} is the value of portfolio at day t.

3. The daily rate of yield on three month US treasury bills are retrieved from http://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/TextView.aspx?data=yield. The equation for interest rate return is as follows:

$$R_{it} = \ln I_t - \ln I_{(t-1)}$$

where I_t is the rate of yield on three month US treasury bills in day t.

4. We use Dow Jones Equity all REIT Total as the REITs index which is retrieved from http://finance.yahoo.com/q/hp?s=%5EREIT+Historical+Prices. The return on real estate is constructed as:

$$R_{rt} = \ln R_t - \ln R_{(t-1)}$$

where R_t is the REITs index in day t.

5. The foreign currency exchange rate is retrieved from US Board of Governors of the Federal Reserve System. (http://www.federalreserve.gov/releases/h10/hist/) We select seven equally weighted major currencies to form a basket of currency, in term of one foreign currency to US dollar. To obtain the return on foreign currency, we use the formula

$$R_{Et} = \ln C_t - \ln C_{(t-1)}$$

where C_t is the foreign currency exchange rate (a basket of currency) to US dollar in day t.

List of US banks in the study

Money center banks portfolio	Regional banks portfolio
Bank of America	Bank of New York
Citigroup	Synovus financial
JP Morgan	Webster Financial
Wells Fargo	

Table 1: Descriptive statistics

	LNM	LNR	LNC	LNI	LNPTO	LNPMC	LNPREG
Mean	3.50E-05	0.000243	-3.71E-06	-0.001246	-8.62E-05	-7.73E-06	-9.31E-05
Median	0.000189	0.000366	3.63E-05	0.000000	3.66E-05	0.000000	0.000000
Maximum	0.044845	0.073013	0.006734	0.884607	0.066093	0.215017	0.07139
Minimum	-0.035614	-0.093307	-0.010469	-1.447158	-0.047892	-0.219533	-0.087653
Std. Dev.	0.005372	0.010000	0.000952	0.075344	0.007520	0.014146	0.010765
Skewness	-0.111103	0.205305	-1.030919	-0.947313	0.298017	0.223083	-0.083866
Kurtosis	9.828445	15.71657	15.07549	82.32645	13.72650	61.856	13.38257
Jarque-Bera	5319.237	18447.53	17101.58	717513.1	13152.27	394777.7	12287.65
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	0.095787	0.663413	-0.010144	-3.406463	-0.235771	-0.021146	-0.254587
Sum Sq. Dev.	0.078888	0.273399	0.002480	15.52012	0.154605	0.547107	0.316856
Observations	2735	2735	2735	2735	2735	2735	2735

Note: LNM is the market return. LNC represents exchange rate return. LNI is the innovation of interest rate. LNR is real estate return. LNRJ is the portfolio of all banks return. LNPMC is the portfolio of large money center banks return. LNPREG is the portfolio of regional banks return.

Table 2 OLS testing result for two models

	Models		Model	
	3 index	4 index	3 index	4 index
	Adjusted R-square	Adjusted R-square	*F statistics	*F statistics
Prior Crisis				
Bank of America	0.422	0.426	354.14	270.92
Citigroup	0.492	0.492	469.55	352.71
JP Morgan	0.473	0.474	435.93	327.51
Wells Fargo	0.384	0.395	302.79	235.90
Webster	0.323	0.356	231.60	201.74
Bank of New York	0.381	0.387	299.37	230.00
Synovus financial	0.415	0.421	344.48	265.63
Overall banks	0.402	0.408	326.54	251.11
Portfolio of Money center	0.227	0.228	143.42	108.44
Portfolio of regional banks	0.513	0.531	511.33	412.87
After Crisis				
Bank of America	0.409	0.473	296.45	288.62
Citigroup	0.357	0.400	237.66	214.33
JP Morgan	0.494	0.555	418.26	399.44
Wells Fargo	0.418	0.502	306.89	324.15
Webster	0.376	0.419	257.99	231.60
Bank of New York	0.497	0.534	422.67	367.73
Synovus financial	0.261	0.328	151.41	156.97
Portfolio of all banks	0.481	0.554	397.01	398.44
Portfolio of Money center banks	0.395	0.459	279.81	272.71
Portfolio of regional banks	0.515	0.582	454.33	447.02

*Significant at 10%

Table 3 Coefficient matrix

	LNC	LNI	LNM	LNR
LNC	1.00	0.09	0.22	0.16
LNI	0.09	1.00	0.07	0.03
LNM	0.22	0.07	1.00	0.71
LNR	0.16	0.03	0.71	1.00

Note: LNM is the market return. LNR is real estate return. LNRJ is the US banks stocks portfolio J return. LNC represents exchange rate return. LNI is the innovation of interest rate.

Table 4

Dependent variable	Adjusted R^2
LNM	0.52
LNC	0.05
LNI	0.01
LNR	0.51

Table 5 Residual Test:

	Breusch-Godfrey		JB test		ARCH test	
	F-statistic	P-value	F-statistic	P-value	F-statistic	P-value
Before the crisis						
Bank of America	6.01	0.00	26,952	0.00	8.58	0.00
Citigroup	3.09	0.08	67,409	0.00	80.24	0.00
JP Morgan	0.00	0.99	45,247	0.00	39.81	0.00
Wells Fargo	302.79	0.66	2,597	0.00	8.23	0.00
Webster	0.04	0.85	1,076	0.00	22.77	0.00
Bank of New York	0.72	0.40	27,882	0.00	48.62	0.00
Synovus financial	9.11	0.00	24,459	0.00	6.78	0.01
Overall banks	113.99	0.00	1,134,277	0.00	457.45	0.00
Portfolio of Money center	262.55	0.00	3,667,330	0.00	475.25	0.00
Portfolio of regional banks	1.75	0.19	6,511	0.00	37.26	0.00
After Crisis						
Bank of America	2.93	0.09	17,827	0.00	72.53	0.00
Citigroup	6.92	0.00	39,441	0.00	92.86	0.00
JP Morgan	2.00	0.16	11,370	0.00	119.73	0.00
Wells Fargo	2.70	0.10	22,304	0.00	17.80	0.00
Webster	12.04	0.00	9,079	0.00	107.43	0.00
Bank of New York	0.27	0.60	11,103	0.00	142.41	0.00
Synovus financial	0.03	0.87	2,022	0.00	68.06	0.00
Overal banks	13.21	0.00	129,172	0.00	216.32	0.00
Portfoliio of Money center	44.30	0.00	620,253	0.00	350.92	0.00
Portfoliio of regional banks	2.02	0.16	7,192	0.00	12.44	0.00

Table 6 OLS estimates

	β_{oj}	β_{Rj}	β_{Mj}	β_{Ij}	β_{ej}	$\overline{R^2}$*	F*
Before the Crisis							
Bank of America	8.97E-05	0.10	0.77	5.56E-03	0.13	0.43	270.92
	(-0.38)	(0.00)	(0.00)	(0.74)	(0.38)		
Citigroup	-6.97E-05	0.04	1.18	-1.58E-02	0.08	0.49	352.71
	(0.60)	(0.21)	(0.00)	(0.46)	(0.67)		
JP Morgan	-2.73E-05	0.07	1.34	1.63E-02	0.15	0.47	327.51
	(0.86)	(0.10)	(0.00)	(0.52)	(0.53)		
Wells Fargo	-2.9E-03	0.47	0.92	5.54E-04	0.33	0.42	231.60
	(0.46)	(0.00)	(0.00)	(0.88)	(0.36)		
Webster	2.44E-05	0.25	0.58	-1.78E-02	0.04	0.36	201.74
	(0.82)	(0.00)	(0.00)	(0.31)	(0.78)		
Bank of New York	-8.84E-05	0.15	1.05	-2.84E-03	-0.12	0.39	230.00
	(0.57)	(0.00)	(0.00)	(0.91)	(0.61)		
Synovus financial	-5.36E-05	0.14	0.94	3.23E-02	0.12	0.42	265.63
	(0.68)	(0.00)	(0.00)	(0.12)	(0.53)		
Portfolio of all Banks	2.34E-06	0.13	0.89	9.44E-03	0.03	0.41	251.11
	(0.99)	(0.00)	(0.00)	(0.64)	(0.88)		
Portfolio of Money center	2.71E-05	0.09	0.94	1.55E-02	0.03	0.23	108.44
	(0.89)	(0.09)	(0.00)	(0.63)	(0.91)		
Portfolio of regional banks	-3.54E-05	0.19	0.82	2.55E-03	0.03	0.53	412.87
	(0.71)	(0.00)	(0.00)	(0.87)	(0.82)		

	β_{oj}	β_{Rj}	β_{Mj}	β_{Ij}	β_{ej}	$\overline{R^2}$*	F*
After the crisis							
Bank of America	-7.14E-3	0.66	0.97	1.35E-03	4.99E-04	0.47	288.62
	(0.10)	(0.00)	(0.00)	(0.73)	(0.999)		
Citigroup	-1.01E-03	0.58	1.06	9.99E-03	0.38	0.40	214.33
	(0.04)	(0.00)	(0.00)	(0.03)	(0.39)		
JP Morgan	-1.19E-04	0.48	0.92	7.85E-03	-0.73	0.55	399.44
	(0.69)	(0.00)	(0.00)	(0.00)	(0.01)		
Wells Fargo	-1.53E-04	0.62	0.71	2.07E-03	-1.00	0.50	324.15
	(0.66)	(0.00)	(0.00)	(0.51)	(0.00)		
Webster	-2.9E-03	0.47	0.92	5.54E-04	0.33	0.42	231.60
	(0.12)	(0.00)	(0.00)	(0.88)	(0.36)		
Bank of New York	-3.26E-04	0.36	1.10	1.26E-03	-1.35	0.53	367.73
	(0.26)	(0.00)	(0.00)	(0.64)	(0.00)		
Synovus financial	-7.64E-3	0.68	0.51	-6.68E-03	0.36	0.33	156.97
	(0.42)	(0.00)	(0.00)	(0.14)	(0.42)		
Portfolio of all banks	-3.51E-04	0.53	0.84	2.58E-03	-0.58	0.55	398.44
	(0.25)	(0.00)	(0.00)	(0.35)	(0.03)		
Portfolio of Money center	-3.18E-3	0.57	0.84	4.50E-03	-0.65	0.46	272.71
	(0.41)	(0.00)	(0.00)	(0.20)	(0.06)		
Portfolio of regional banks	-4.16E-04	0.46	0.85	-6.53E-04	-0.48	0.58	447.02
	(0.12)	(0.00)	(0.00)	(0.79)	(0.05)		

Notes: The model is

$$\mathbf{R_{jt} = \beta_{oj} + \beta_{mj}R_{mj} + \beta_{Ij}R_{Ij} + \beta_{ej}R_{ej} + \beta_{Rj}R_{Rj} + \epsilon_{jt}}$$

* Values in parentheses are p-value, $\overline{\mathbf{R^2}}$ is the adjusted R square. The F statistic is for a test of overall significance: all F statistics are significant at the 5%.

Table 7 Maximum likelihood estimation of GARCH(1,1)-Models

	BA	Citi	JP	WF	Web	BNY	SF	OV	PMC	PRB
Before the crisis										
$\beta_j(10^{-4})$	1.65	-3.07	1.51	0.16	2.93	-2.97	0.08	10.82	27.95	0.32
	(0.49)	(0.88)	(0.48)	(0.95)	(0.31)	(0.48)	(0.97)	(0.00)	(0.00)	(0.88)
β_{ej}	0.01	0.10	0.07	-0.03	-0.01	0.15	0.02	0.16	-0.43	0.05
	(0.92)	(0.45)	(0.63)	(0.80)	(0.96)	(0.47)	(0.89)	(0.05)	(0.10)	(0.65)
β_{Rj}	0.12	0.03	0.08	0.09	0.24	0.15	0.14	0.10	0.35	0.19
	(0.00)	(0.32)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
β_{mj}	0.74	1.01	1.08	0.69	0.58	1.10	0.86	0.90	0.73	0.78
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\beta_{Ij}(10^{-1})$	0.00	-3.69	-1.22	-0.36	-1.21	0.33	3.88	-5.60	5.10	-0.51
	(0.26)	(0.03)	(0.49)	(0.79)	(0.43)	(0.88)	(0.02)	(0.00)	(0.07)	(0.73)
$\beta_{oj}(10^{-2})$	0.18	-0.04	0.18	0.03	0.33	-0.33	0.00	1.24	2.82	0.04
	(0.50)	(0.87)	(0.46)	(0.92)	(0.30)	(0.46)	(0.99)	(0.00)	(0.00)	(0.88)
φ_1	0.20	0.06	0.04	0.04	0.13	0.41	0.16	2.05	0.87	0.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ρ_1	0.75	0.93	0.95	0.95	0.79	0.28	0.83	0.03	-0.01	0.94
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.00)
$\omega(10^{-6})$	1.23	0.19	0.12	0.18	1.49	13.60	0.70	4.67	24.40	0.19
	(0.00)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\overline{R^2}$	0.42	0.48	0.46	0.39	0.36	0.39	0.42	0.40	0.26	0.53

	BA	Citi	JP	WF	Web	BNY	SF	OV	PMC	PRB
After the Crisis										
$\beta_j(10^{-4})$	5.59	9.32	7.05	5.83	12.86	0.05	3.37	5.77	1.21	4.64
	(0.10)	(0.04)	(0.09)	(0.14)	(0.02)	(0.99)	(0.50)	(0.08)	(0.64)	(0.10)
β_{ej}	-0.25	0.07	-0.17	-0.71	-0.52	-0.56	-0.20	-0.53	-0.25	-0.39
	(0.30)	(0.81)	(0.44)	(0.00)	(0.05)	(0.01)	(0.59)	(0.01)	(0.27)	(0.05)
β_{rj}	0.50	0.42	0.44	0.46	0.38	0.31	0.62	0.43	0.44	0.42
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
β_{mj}	0.78	1.01	0.80	0.84	1.09	0.96	0.64	0.89	0.83	0.91
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\beta_{Ij}(10^{-2})$	-0.22	-0.97	-0.12	0.15	0.15	0.10	-0.76	-0.01	4.04	2.56
	(0.33)	(0.00)	(0.56)	(0.88)	(0.48)	(0.39)	(0.03)	(0.93)	(0.00)	(0.00)
$\beta_{oj}(10^{-3})$	-2.19	-9.67	-1.17	1.46	1.45	0.97	-7.61	-0.14	40.39	25.64
	(0.17)	(0.07)	(0.10)	(0.13)	(0.02)	(0.99)	(0.58)	(0.11)	(0.27)	(0.15)
φ_1	0.16	0.19	0.12	0.19	0.07	0.23	0.06	0.10	0.57	0.47
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ρ_1	0.84	0.79	0.86	0.81	0.92	0.77	0.94	0.90	0.90	0.66
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\omega(10^{-6})$	2.26	5.56	2.54	2.39	1.93	2.78	1.02	0.88	3.34	3.61
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)
$\overline{R^2}$	0.45	0.37	0.55	0.49	0.41	0.52	0.32	0.58	0.40	0.52

The GARCH(1,1)-M models estimated as follows,

$$R_{jt} = \beta_{oj} + \beta_{mj}R_{mj} + \beta_{Ij}R_{Ij} + \beta_{ej}R_{ej} + \beta_{Rj}R_{Rj} + \beta_j \log h_t + \epsilon_{jt} \quad (2)$$

$$\epsilon_{jt} = \omega + \partial_0 + \partial_1 \in_{jt-1}$$
$$h_t = \omega + \varphi_1 \epsilon_{t-1}^2 + \rho_1 h_{t-1} \quad (3)$$

BA is banks of America; Citi denotes Citigroup; JP is JP Morgan; WF is Wells Fargo; Web is Webster Financial; BNY is banks of New York; SF is Synovus financial; OV is portfolio of all individual banks; PMC is the portfolio of money center; PRB is the portfolio of regional banks.

Table 8 P-values for tests of H2

	BA	Citi	JP	WF	Web	BNY	SF	OV	PMC	PRB
Before Crisis										
F-statistic*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chi-square*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
After Crisis										
F-statistic*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chi-square*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

*Note: Eviews report both the Chi-square and F-statistic statistics. The resulting p-values as shown in this table are all 0.

Table 9 P-values for tests of H4

	BA	Citi	JP	WF	Web	BNY	SF	OV	PMC	PRB
From Jan 03.2002-June 26.2012										
F-statistic*	0.0353	0.00	0.0692	0.00	0.00	0.39	0.00	0.00	0.00	0.0001
Chi-square*	0.0352	0.00	0.0692	0.00	0.00	0.39	0.00	0.00	0.00	0.0001

*Note: Eviews report both the Chi-square and F-statistic statistics. The resulting p-values are shown in this table

Table 10 Maximum likelihood estimates of GARCH (1,1)-M models of with conditional volatility of real estate return over the impact of financial crisis. (From Jan 03.2002-June 26. 2012)

	BA	Citi	JP	WF	Web	BNY	SF	OV	PMC	PRB
$\beta_j(10^{-4})$	-1.24	-2.23	0.59	0.89	0.61	-0.62	-1.07	0.30	2.19	-0.91
	(0.24)	(0.05)	(0.65)	(0.42)	(0.66)	(0.77)	(0.34)	(0.74)	(0.00)	(0.38)
β_{ej}	0.05	0.17	-0.06	-0.13	0.11	-0.22	0.08	-0.23	-0.77	-0.03
	(0.64)	(0.15)	(0.58)	(0.24)	(0.42)	(0.15)	(0.54)	(0.02)	(0.00)	(0.76)
β_{Rj}	0.24	0.14	0.21	0.22	0.34	0.23	0.24	0.27	0.52	0.30
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
β_{mj}	0.76	1.04	1.04	0.74	0.62	0.99	0.85	0.90	0.60	0.79
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\beta_{Ij}(10^{-3})$	-3.13	-9.52	-0.84	1.79	-0.94	0.37	-4.86	20.69	38.20	0.07
	(0.15)	(0.00)	(0.65)	(0.35)	(0.63)	(0.76)	(0.13)	(0.00)	(0.00)	(0.96)
$\beta_{oj}(10^{-3})$	-1.59	-2.66	0	1.07	0.61	-0.74	-1.26	-0.12	1.01	-1.12
	(0.18)	(0.00)	(0.21)	(0.39)	(0.69)	(0.74)	(0.31)	(0.91)	(0.91)	(0.35)
φ_1	0.18	0.10	0.06	0.13	0.09	0.07	0.12	0.67	2.04	0.09
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$d(10^{-6})$	2.63	2.09	0.69	2.00	3.88	-0.14	3.75	4.99	6.78	0.84
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.19)	(0.00)	(0.00)	(0.00)	(0.00)
$\delta(10^{-5})$	-7.27	-2.63	3.67	-1.08	11.1	23.7	-13.9	-33.9	97.4	2.18
	(0.02)	(0.41)	(0.03)	(0.69)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.25)
ρ_1	0.81	0.89	0.93	0.84	0.87	0.91	0.87	0.54	0.16	0.89
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\omega(10^{-7})$	9.61	4.76	0.87	6.34	3.24	0.891	10.2	40.3	49.7	2.24
	(0.00)	(0.00)	(0.21)	(0.00)	(0.01)	(0.32)	(0.00)	(0.00)	(0.00)	(0.00)
$\overline{R^2}$	0.37	0.33	0.50	0.41	0.38	0.48	0.30	0.48	0.36	0.55

The GARCH(1,1)-M models estimated as follows,

$$R_{jt} = \beta_{oj} + \beta_{mj}R_{mj} + \beta_{Ij}R_{Ij} + \beta_{ej}R_{ej} + \beta_{Rj}R_{Rj} + \beta_j \log h_t + \epsilon_{jt} \qquad (2)$$

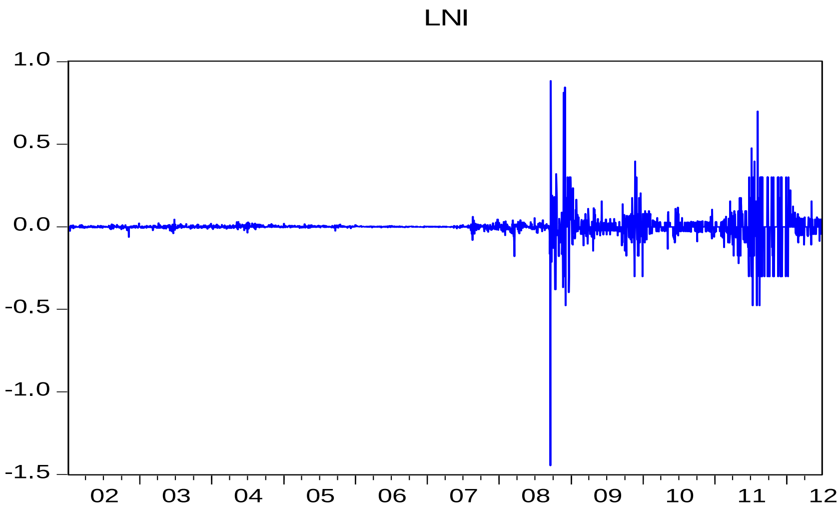
$$\epsilon_{jt} = \omega + \partial_0 + \partial_1 \in_{jt-1}$$

$$h_t = \omega + \varphi_1\epsilon^2_{t-1} + \rho_1 h_{t-1} + dD + \delta CR_{t-1} \qquad (4)$$

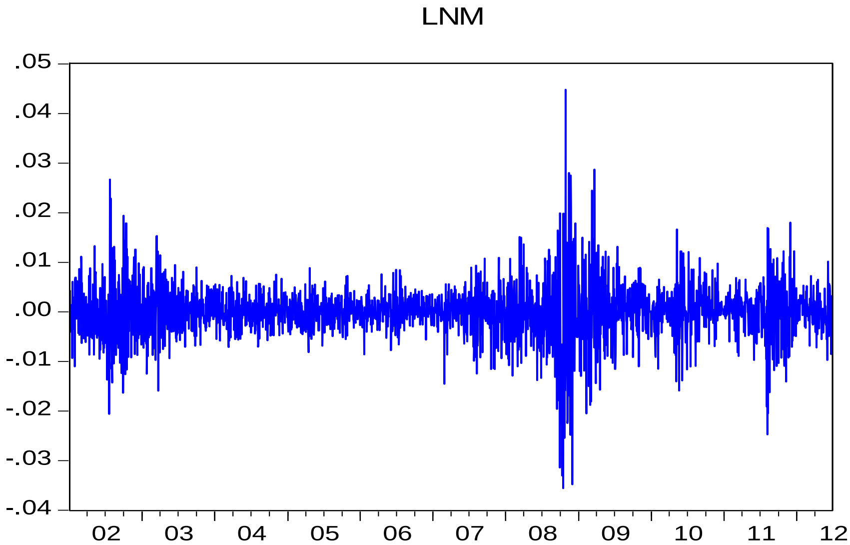
BA is banks of America; Citi denotes Citigroup; JP is JP Morgan; WF is Wells Fargo; Web is Webster Financial; BNY is banks of New York; SF is Synovus financial; OV is portfolio of all individual banks; PMC is the portfolio of money center; PRB is the portfolio of regional banks.

Appendix. Graph

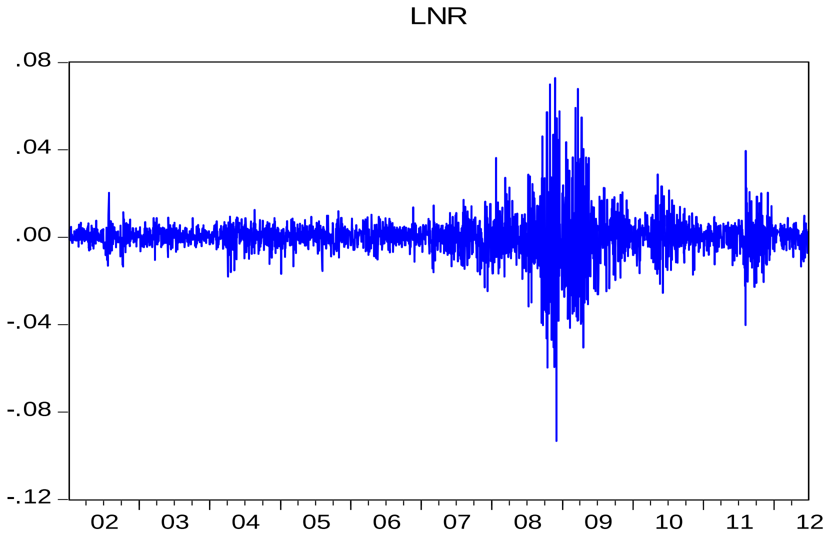
Graph 1. Time-series plot of the interest return



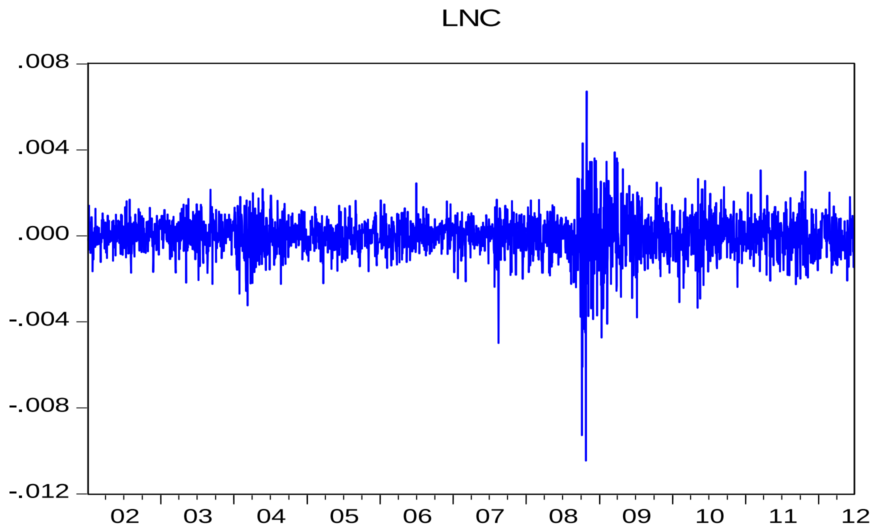
Graph 2 time series plot of the market return



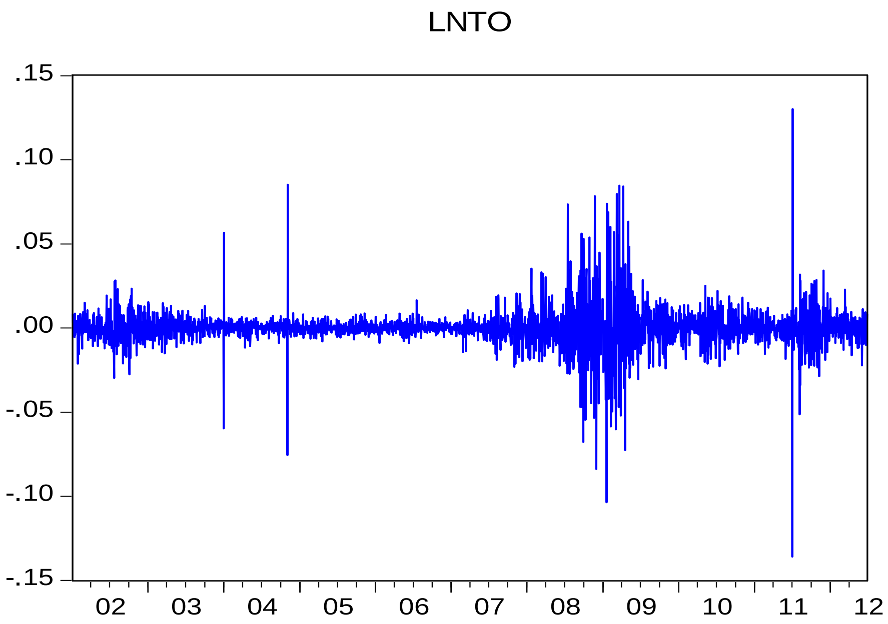
Graph 3 time-series plot of real estate return



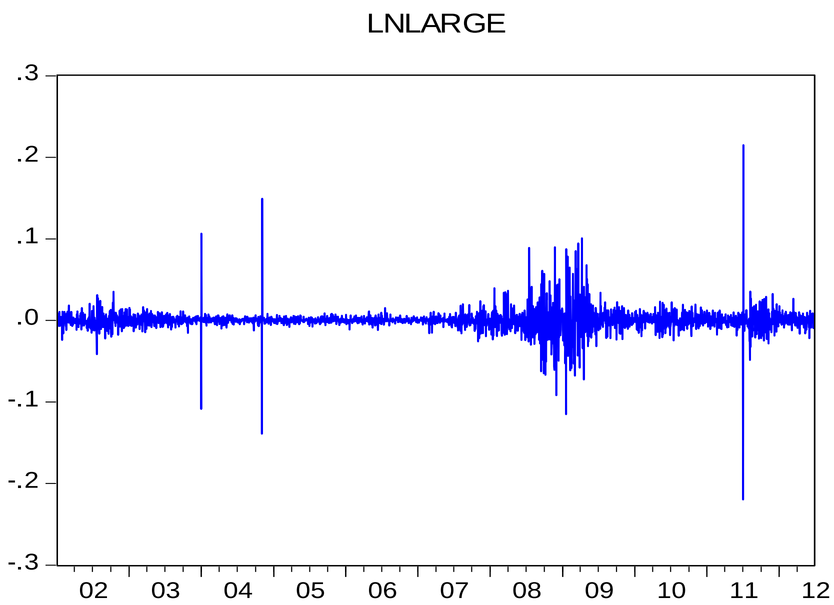
Graph 4. Time series plot of foreign exchange return



Graph 5 Time series plot of return on portfolio of all banks



Graph 6 Time series plot return on portfolio of large money center banks



Graph 7. Times series plot of return on portfolio of regional banks