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# Flight to Quality for Large Financial Institutions

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Local correlation analysis is used to investigate flight to quality among large financial institutions before, during, and after the financial crisis of 2008-2009. While standard correlation captures general overall linear association, local correlation analysis more accurately captures changes in the associations in response to changing market conditions. Using raw, market-adjusted, and industry-adjusted stock returns of individual banks, we investigate the performance of troubled banks and the change in investing behavior. Investors react to noisy information from the financial difficulties encountered by banking institutions. This reaction results in flight to quality. While the traditional Pearson correlations capture general overall linear association, local correlation analysis captures changes in the association in response to changing market conditions. Thus, local correlation analysis more accurately measures changes in correlation where it matters most: in the loss tail of the distribution of financial returns; leading to more appropriate diversification, portfolio management, and within-industry implications.

*JEL classification*: G01; G20; G21
*Keywords*: Flight to quality, Local correlation, Financial Institutions

## 1. Introduction

Dramatic changes in financial markets over the past two decades have attracted the attention of many researchers. Studies on contagion and flight to quality in banking mostly focus on systemic risk or the behavior of representative institutions (e.g., de Bandt, *et al*., 2009; Acharya, *et al*., 2010). Following heterogeneous agent theory (Hommes, 2006), this study investigates flight to quality by tracking the reaction of investors to the recent banking crisis in the U. S.

To investigate capital flight experienced by different economic agents, it is necessary to take into consideration that each agent experiences a change in behavior over time. Commonly used statistical tools are poorly equipped to analyze the volatile relationship among agents. Local correlation analysis developed by (Bradley and Taqqu, 2005a, and Bradley and Taqqu, 2005b) allows for the examination of flight to quality as the crisis spread from one large weak financial institution to the next. The essence of local correlation analysis is that it captures the change in correlation between financial institutions during times of typical performance as compared to periods of atypical performance. Also, local correlation analysis is more sensitive to changing financial market conditions whereas the Pearson correlation coefficient is more of a general average of association over the time period of interest.

In short, this research separates itself from other banking studies by analyzing individual banks, rather than modeling a representative institution or banking markets. More importantly, it demonstrates that local correlation analysis is a powerful tool for revealing the existence of flight to quality among competing banks. Following this introduction, the next section reviews the current literature. Our methodology is explained in Section 3. The subsequent section provides the findings of our analysis. Conclusions are given in the last section.

## 2. Literature Review

As pointed out by de Bandt *et al*. (2009), systemic risk can be reduced to three forms: the contagion risk due to widespread idiosyncratic problems, the risk attributable to macro shocks, and the risk resulting from imbalances built up in a system. Financial institutions are very sensitive to the systemic risk because of their susceptibility to changes in information, their concern for leverage and maturity mismatches, and their interconnectedness to daily operations.

In the economics literature, there are several strands of studies on banking crises. Tracing the causes of banking crises, some studies focus on bank runs triggered by the decrease in value of bank assets and the asset-liability maturity mismatch (Rochet and Vices, 2004). An issue related to bank balance sheets is the intertemporal character of financial contracts, which often threatens the survival of creditors as well as debtors (de Bandt *et al.*, 2009). Once a banking institution is perceived as having difficulty in fulfilling its financial obligations to depositors and creditors, this financial trouble can quickly affect other banks because of the existence of complex and closely related networking relationships (Allen and Gale 2000). Moreover, many researchers suggest that uncertainty due to unusual events and risky financial innovations are behind the banking crises in recent years (Holmstrom and Tirole, 1998; Caballero and Krishnamurthy, 2008). Facing Knightian uncertainty resulting from major financial or political events, financial intermediaries and businesses choose to hoard extra amounts of liquidity. Their inability of effective judgment of the riskiness of their investments leads to financial crises. The ex-ante aspect is related to the fact that banks have similar or correlated assets as well as liabilities. The ex-post aspect suggests that the failure of one bank transmits adverse information throughout the system, and results in the herding behavior of moving assets to safer financial institutions according to Acharya and Yorulmazer (2008). They document that the ex-ante anticipation of systemic risk in banking may imply contagion, while the ex-post aspect may result in flight to quality.

Three alternative methods are used to measure the impact of a change in systemic risk in the literature. In the first method, researchers apply cross-correlation analysis of bank failures to measure the extent of the systemic risk. The second uses the survival time of banks as an indicator of risk. And the third approach analyzes equity price data or bank returns. Acharya and Yorulmazer (2003), Goldstein and Pauzner (2005), Moheeput (2008), as well as Gropp *et al.* (2009) have used stock returns to detect the extent of systemic risk. Depending on the theoretical framework and experimental design, a wide variety of methods have been used to investigate financial crises in the literature. Some of the commonly used techniques are instrumental variable regression analysis (e.g., Pick, 2007), probit (e.g., Hasan and Dwyer, 1994), autoregressive Poison regression (e.g., Schoenmaker, 1996), multinomial logit (Gropp *et al.*, 2009), seemingly unrelated regressions (e.g., Smirlock and Kaufold, 1987), OLS cross-section regression (e.g., Musumeci and Sinkey, 1990), Generalized Least Squares (GLS) cross-section regression (e.g., Karafiath *et al.*, 1991), simulation analysis (Moheeput, 2008); network topology (e.g., Markose *et al.*, 2009), conditional value-at-risk (Adrian and Brunnermeier, 2009), and systemic expected shortfall (Acharya *et al.*, 2010).

To avoid complications associated with institutional size and international variations, but to also properly address the issue of correlation breakdown, we examine flight to quality among large financial institutions in the U.S. using the local correlation approach proposed by Bradley and Taqqu (2005a). With this methodology we inherently conjecture that the correlation structure is dynamic and that it changes at the extreme loss (negative stock return) events such as financial crises.

## 3. Methodology

In their seminal work, Bradley and Taqqu (2004) have developed a methodology for measuring the local correlation between two data series. Given two series, $Z = (z_a, a = 1, 2, \ldots, n)$ and $Y = (y_a, a = 1, 2, \ldots, n)$, the regression of $Y$ on $Z$ can be stated as follows:

$$Y = \alpha + \beta(Z)\, Z + \sigma(Z)\, \varepsilon, \tag{1}$$

where $\alpha$ stands for the vertical intercept, $\beta(Z)$ is the slope of the regression function, $\varepsilon \sim N(0, 1)$ represents the noise which is independent of $Z$, and $\sigma^2(Z)$ depicts the residual variance. This can be restated as

$$Y = m(Z) + \sigma(Z)\, \varepsilon, \tag{2}$$

where $m(Z)$ denotes the expected value of $Y$. Given a specific value $z$ of $Z$, the above equations suggest $m(z) = E(Y \mid Z = z) = a + \beta(z)z$. $\beta(z)$ can be interpreted as the slope of $m(z)$. This slope can also be denoted by $m'(z)$. At $Z = z$, the local correlation between $Y$ and $Z$ is:

$$\rho(z) = \beta(z)\frac{\sigma_z}{\sigma_y} = \frac{\sigma_z \beta(z)}{\left[\sigma_z^2 \beta^2(z) + \sigma^2(z)\right]^{1/2}}, \tag{3}$$

where $\sigma_z$ and $\sigma_y$ are the standard deviations of $Z$ and $Y$, respectively, and the residual variance is $\sigma^2(z)$.

Mathur (1998) has proposed the use of polynomial functions in correlation analysis. Bradley and Taqqu (2005a, 2005b) have applied this technique to estimate $\beta(z)$ which is estimated by using local polynomial regression. Let $m(z)$ be a smooth and quadratic function. Its Taylor series expansion about a target point $z_0$ is approximately $m(z_0) + m'(z_0)(z-z_0)+\ldots+m^{(q)}(z_0)/q!(z-z_0)^q$. By solving the following weighted least squares problem,

$$\min_{\beta(z_0)}[(Y - Z_q(z_0)\beta(z_0))^T W_h(z_0)(Y - Z_q(z_0)\beta(z_0))], \tag{4}$$

one can estimate $m^{(k)}(z_0)/k!$ (or, $\beta_k(z_0)$). In the above equation, the rows of $Z_q$ are $[1\ (Z_k-z_0)\ \ldots\ (Z_k-z_0)^q]$, $k = 1, 2, \ldots, n$; and the nonzero diagonal elements of the weighting matrix $W_h(.)$, $K(z_t - z_0)/h^2$, are determined with the Epanechnikov kernel, $K$, and bandwidth, $h$. By optimally minimizing the asymptotic mean square error, the values of K and $h$ can be properly chosen for local polynomial fitting (for details, see Bjerve and Doksum, 1993). Solving (4), one can obtain the vector of estimates $\hat{\beta}(z_0) = \{Z_q(z_0)^T W_h(z_0) Z_q(z_0)\}^{-1} Z_q(z_0)^T W_h(z_0) Y$.

The above procedure also allows us to estimate the local residual variance, $\sigma^2(z)$. At any target point $z_0$,

$$\hat{\sigma}^2(z_0) = e_1^T \Lambda u^2 / (1 + e_1^T \Lambda \Delta). \tag{5}$$

In this equation, $e_1$ is a unit vector whose first element is $1$, and $u$ denotes the vector of estimated residuals from (4), which is the difference between $Y$ and $\hat{m}(z)$. In addition, $\Delta$ represents a vector of diagonal elements of a matrix which measures any potential bias in the estimated coefficients, and $\Lambda = \{Z_q(z_0)^T W_h(z_0) Z_q(z_0)\}^{-1} Z_q(z_0)^T W_h(z_0)$.

There are two assumptions underlying the procedures proposed by Bradley and Taqqu (2005b). Let $z_M$ be the median of the distribution of $Z$, and $z_L$ a low quantile of this distribution

One of their assumptions is that the estimate $\hat{\rho}(z_L)$ of $\rho(z_L)$ is independent of the estimate $\hat{\rho}(z_M)$ of $\rho(z_M)$. These estimates are viewed as independent if data sets with no overlapping data points are used for their computation. In other words, one cannot use a data point $(z_a, y_a)$ to compute both $\hat{\rho}(z_M)$ and $\hat{\rho}(z_L)$. It is a rare occurrence that the same data points are used for computing both unless the low quantile of a distribution is equal to or very close to its median. If this condition cannot be met, the common points used for the estimation of both should have very small weights assigned.

The other assumption is that the estimated local correlation coefficients of both $\hat{\rho}(z_L)$ and $\hat{\rho}(z_M)$ are normally distributed. This assumption requires the removal of any serial dependencies within and between the series. The use of a vector autoregressive model is often considered as a reasonable approach to remove serial dependency. A two-dimensional vector autoregressive model, $VAR(p)$, with $p = 1, \ldots, n$, is

$$\Phi(B) r_a = \phi_0 + v_a, \tag{6}$$

where $r_a = [z_a, y_a]^T$, $B$ is the back-shift operator, and $v_a$ are residuals for $p$ up to $n$.

According to Bradley and Taqqu (2004, 2005a, 2005b), a Quantile-Quantile (QQ) plot can be used to determine whether the bootstrapped distribution of $\hat{\rho}(z_L)$ approaches a normal distribution, while a Probability-Probability (PP) plot is a tool for determining whether the bootstrapped distribution of $\hat{\rho}(z_M)$ can be well approximated by a normal distribution.

When the local correlation in the loss tail of a distribution is lower than that in the center, there is a financial flight to quality from $Z$ to $Y$. That is,

$H_0$: $\rho(z_L) \geq \rho(z_M)$ no flight to quality, and

$H_1$: $\rho(z_L) < \rho(z_M)$ flight to quality.

Given $\hat{\sigma}^2_{\hat{\rho}(z_L)}$ and $\hat{\sigma}^2_{\hat{\rho}(z_M)}$ as the estimates of $\sigma^2_{\rho(z_L)}$ and $\sigma^2_{\rho(z_M)}$, respectively, the test statistic for determining the acceptance of the null hypothesis is:

$$T = \frac{\hat{\rho}(z_L) - \hat{\rho}(z_M)}{\left[\hat{\sigma}^2_{\hat{\rho}(z_L)} + \hat{\sigma}^2_{\hat{\rho}(z_M)}\right]^{1/2}}. \tag{7}$$

Let $\hat{T}$ be the estimated value of $T$. If $\hat{T} < -t_{1-a}$, then $H_0$ is rejected, where $t_{1-a}$ is the $1-\alpha$ quantile of the standard normal distribution.

**4. Data and Findings**

Our data are from the CRSP database. We examine twelve major U.S. financial institutions; namely Bear-Stearns (BSC), Lehman Brothers (LEH), Washington Mutual (WAMU), Merrill-Lynch (MER), Wachovia Bank (WB), Wells Fargo (WFC), Goldman Sachs (GS), Bank of America (BAC), Citigroup (C), J.P. Morgan (JPM), Morgan Stanley (MS), and American Insurance Group (AIG). The first five have either gone bankrupt or had been in such poor financial health that they were rescued / acquired by other banks during the financial crises of 2008-2009. The last seven in our list were the largest banks in the U.S. financial sector before the crisis. According to the Office of the Comptroller of the Currency OCC (2011) report, with the exception of AIG, these banks continue to be the pillars of the financial sector in the U.S. economy.

We use daily return data for these twelve banks in our investigation of flight to quality from poorly performing banks to others. The sample period is from 2002 through 2011. Our sample data both precede and extend beyond the recent financial crisis. This enables us to examine the local correlation relationships and measure flight to quality from poor banks to others attributable to the financial crisis. The sample period includes the last trading day of all the poorly performing banks. For Bears-Stearns the last day of trade was June 2, 2008, while the last trading days were September 17, 2008 for Lehman, September 26, 2008 for Washington Mutual, and January 2, 2009 for Wachovia Bank, as well as for Merrill Lynch.

The CRSP daily return data include dividends. We also conduct our investigation using returns without dividends and report these results. These returns are calculated by dividing the end-of-day price and beginning-of-day price differences by their corresponding end-of-day prices. Alternatively, returns based on log differences of prices are also applied. These log returns lead to the same conclusions. Therefore, for brevity we do not report them in the paper.

We examine flight to quality effects using the above raw returns. In addition, the local correlation between banks is examined using abnormal returns. For each bank, we compute the difference between the bank return and the market return. To this end, two types of market returns provided by CRSP are used: market returns based on the equally-weighted index and the value weighted index using all issues traded at NYSE, Amex, NASDAQ, and Arca stock exchanges.

Finally, we also investigate abnormal returns for the twelve banks by using a banking sector return index rather than the total market return. The bank index returns are calculated from the PHLX KBW Bank Sector Index, which is a capitalization-weighted index composed of 24 geographically diverse stocks representing national money center banks and leading regional institutions. This index is based on one-tenth the value of the value of the Keefe, Bruyette & Woods Index (KBW). Founded in 1962, Keefe, Bruyette & Woods follow more than 200 commercial banking and thrift industries on a daily basis, and have long been recognized by banking industry experts.

**Table 1. Summary Statistics**

| | Mean | Std. Dev. | Skewness | Kurtosis |
|---|---|---|---|---|
| **Panel A. Returns with dividends** | | | | |
| WFC | 0.0727 | 3.0702 | 2.0050 | 29.7934 |
| GS | 0.0634 | 2.6098 | 1.0145 | 20.0026 |
| BAC | 0.0400 | 3.5751 | 1.0542 | 27.4198 |
| C | -0.0134 | 3.9487 | 1.5924 | 42.0380 |
| JPM | 0.0636 | 2.9922 | 0.9427 | 16.6220 |
| MS | 0.0619 | 3.9171 | 5.0890 | 118.9849 |
| AIG | -0.0122 | 5.0779 | 1.3627 | 49.1482 |
| LEH | -0.1298 | 4.4481 | -6.6923 | 159.4719 |
| BSC | -0.0028 | 3.8271 | 0.1725 | 338.8321 |
| MER | -0.0216 | 3.3597 | 1.2424 | 31.5045 |
| WAMU | -0.1404 | 4.3651 | -4.4679 | 134.4830 |
| WB | 0.0506 | 4.8442 | 3.4082 | 148.0819 |
| **Panel B. Returns excluding dividends** | | | | |
| | Mean | Std. Dev. | Skewness | Kurtosis |
| WFC | 0.0615 | 3.0748 | 1.9942 | 29.6570 |
| GS | 0.0599 | 2.6106 | 1.0153 | 19.9882 |
| BAC | 0.0254 | 3.5744 | 1.0628 | 27.4534 |
| C | -0.0247 | 3.9492 | 1.5975 | 42.0400 |
| JPM | 0.0510 | 2.9926 | 0.9452 | 16.6286 |
| MS | 0.0551 | 3.9187 | 5.0702 | 118.8269 |
| AIG | -0.0148 | 5.0775 | 1.3643 | 49.1659 |
| LEH | -0.1334 | 4.4494 | -6.6879 | 159.2796 |
| BSC | -0.0067 | 3.8268 | 0.1750 | 338.9417 |
| MER | -0.0291 | 3.3630 | 1.2382 | 31.4033 |
| WAMU | -0.1565 | 4.3643 | -4.4628 | 134.5071 |
| WB | 0.0356 | 4.8448 | 3.4153 | 148.0585 |
| **Panel C. Market Returns and Banking Sector Index Returns** | | | | |
| | Mean | Std. Dev. | Skewness | Kurtosis |
| VW | 0.0281 | 1.3674 | -0.0275 | 11.5431 |
| EW | 0.0737 | 1.2193 | -0.1414 | 11.4926 |
| KBW | 0.0316 | 2.7250 | 6.7260 | 186.3940 |

**Panel D. Pearson Correlation Coefficients**

| | KBW | WFC | JPM | MER | BAC | AIG | BSC | MS | C | LEH | GS | WB |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WFC | 0.90 | | | | | | | | | | | |
| JPM | 0.88 | 0.79 | | | | | | | | | | |
| MER | 0.83 | 0.72 | 0.75 | | | | | | | | | |
| BAC | 0.89 | 0.84 | 0.78 | 0.81 | | | | | | | | |
| AIG | 0.52 | 0.44 | 0.45 | 0.57 | 0.52 | | | | | | | |
| BSC | 0.41 | 0.32 | 0.28 | 0.47 | 0.36 | 0.34 | | | | | | |
| MS | 0.68 | 0.58 | 0.62 | 0.66 | 0.61 | 0.42 | 0.44 | | | | | |
| C | 0.79 | 0.70 | 0.71 | 0.79 | 0.79 | 0.57 | 0.43 | 0.61 | | | | |
| LEH | 0.62 | 0.54 | 0.54 | 0.66 | 0.64 | 0.68 | 0.52 | 0.63 | 0.61 | | | |
| GS | 0.73 | 0.63 | 0.71 | 0.73 | 0.65 | 0.38 | 0.44 | 0.80 | 0.65 | 0.65 | | |
| WB | 0.73 | 0.62 | 0.58 | 0.61 | 0.66 | 0.56 | 0.36 | 0.45 | 0.55 | 0.66 | 0.44 | |
| WAMU | 0.57 | 0.45 | 0.39 | 0.47 | 0.49 | 0.44 | 0.42 | 0.47 | 0.51 | 0.54 | 0.39 | 0.68 |

Notes: This table presents the unconditional statistics of daily percentage raw returns. Panel A shows summary statistics for returns with dividends included. Panel B is for bank stock returns excluding dividends. Panel C presents summary statistics for value weighted (VW) and equally weighted (EW) market returns along with banking sector index (KBW) returns. Panel D presents the Pearson correlation coefficients.

The summary statistics for the daily returns for each bank are presented in Table 1. Daily returns with and without dividends are shown in Panels A and B. We also report the value weighted daily market returns (VW), equally weighted daily market returns (EW), and bank sector daily returns (KBW) in Panel C.

The mean, standard deviation, skewness, and kurtosis values indicate that although some of the returns series exhibit symmetrical distributions, many others are not symmetrical. Note also that the kurtosis value of each series far exceeds 3. Based upon the summary statistics of our data, it is safe to say that all of the return series are non-normally distributed. Linear regression is a technique which requires the distributions of tested series to be normal. Thus, the statistics on skewness and kurtosis lend support to the use of local correlation. We report the values of the traditional Pearson correlation coefficients in Panel D. We observe that the surviving financial institutions tend to have a stronger overall correlation with the KBW index. We also note that the four institutions with the lowest correlations with the KBW index were all taken over or allowed to fail as in the case of Lehman Brothers.

**4.1. Flight to Quality**

We follow the definition of flight to quality developed in the seminal papers by Bradley and Taqqu (2004, 2005a, 2005b) and Inci *et al*. (2011). That is, financial flight to quality from bank Z to bank Y occurs if the relationship between the two banks decreases when the performance of Z is significantly below its typical performance (Bradley and Taqqu, 2005b, p. 82). Putting it differently, there is a flight to quality from bank Z to bank Y when the dependence becomes lower at the loss tail distribution of Z than at its center. A robust statistic which is well suited for this is local correlation, which is derived from local polynomial regression, and allows for the determination of the reaction in one bank relative to the change in the returns in other banks. We examine flight to quality from troubled banks to others, where a troubled bank is one that was eventually delisted from the stock exchange.[1] Flight to quality suggests the movement of capital from a troubled bank to a safer bank. For example, a large decline in Bear-Stearns stock price results in a contemporaneous flight of capital to safer banks such as Goldman Sachs, or J.P. Morgan Chase.

Flight-to-quality test results in the banking industry are provided in Table 2. In the order of these banks' last trading date, the first panel at the top left examines flight to quality from Bear-Stearns (BSC) to the other 11 banks. The second panel at the top right reveals flight to quality from Lehman (LEH) to the other remaining 10 banks. The middle left panel shows flight to quality from Washington Mutual (WAMU) to the remaining 9 banks. The middle right panel and the panel at the bottom measure flight to quality from Merrill Lynch and Wachovia Bank to the remaining 7 banks. The estimates of the local correlation coefficients, $\hat{\rho}(z_M)$ and $\hat{\rho}(z_L)$, between the troubled bank and safer banks are reported, where $z_M$ is the median of the distribution, and $z_L$ is for the lower quantile (2.5 percentile) of the distribution.[2] Throughout our investigation, the expectation is that the local correlation based on the lower quantile of the return distribution should be more negative (or less positive) compared to that at the median. Then, there is flight to quality from the troubled bank towards a safer bank. The last column provides the test statistic $\hat{T}$ to determine the significance of each flight to quality. The table also provides the estimates of the standard deviations of the local correlation coefficients, $\hat{\sigma}_{\hat{\rho}(z_M)}$ and $\hat{\sigma}_{\hat{\rho}(z_L)}$.

The regression models used in the table assume that the estimators are normally distributed even though the underlying time series is not normally distributed. The distributions of the local correlation estimators are obtained from running the bootstrapping procedure 1000 times and are found to be approximately normal. Each panel in the table reveals the ticker symbol of the tested pairs.

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[1] Bears-Stearns is the first large troubled bank since its last day of trade was June 2, 2008. The second troubled bank is Lehman with its last trading day of September 17, 2008. The third troubled bank, Washington Mutual had its last trading day on September 26, 2008. Finally the last trading day was January 2, 2009 for Wachovia Bank, and Merrill Lynch.

[2] We also used various lower quantile cutoff values up to 5 percentile of the return distributions which led to the same conclusions.

Flight to quality is defined as a weaker dependence, measured in terms of local correlation, in the (loss) tail section of the return distribution than at the center. If the test statistic ($\hat{T}$) is less than -1.65, then there is flight to quality at 5% significance (or less than -2.33 at 1% significance). All the test statistics in Table 2 clearly show that for all five troubled banks, there is strong evidence of contemporaneous flight to quality at the 1% significance level. All of the lower quantile local correlation estimates are below the corresponding median local correlations.

**Table 2. Flight to Quality**

| **BSC to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | **LEH to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| LEH | 0.9524 | 0.0016 | 0.8824 | 0.0155 | -4.49$^{***}$ | WAMU | 0.7951 | 0.0109 | 0.4897 | 0.0561 | -5.34$^{***}$ |
| WAMU | 0.7889 | 0.0124 | 0.6998 | 0.0419 | -2.04$^{**}$ | MER | 0.9296 | 0.0024 | 0.7149 | 0.0281 | -7.61$^{***}$ |
| MER | 0.9382 | 0.0024 | 0.8719 | 0.0187 | -3.53$^{***}$ | WB | 0.8620 | 0.0061 | 0.6528 | 0.0343 | -6.00$^{***}$ |
| WB | 0.8664 | 0.0069 | 0.7693 | 0.0361 | -2.64$^{***}$ | WFC | 0.8640 | 0.0060 | 0.4332 | 0.0587 | -7.30$^{***}$ |
| WFC | 0.8617 | 0.0071 | 0.7728 | 0.0324 | -2.68$^{***}$ | GS | 0.9460 | 0.0018 | 0.4655 | 0.0769 | -6.24$^{***}$ |
| GS | 0.9430 | 0.0021 | 0.8036 | 0.0314 | -4.43$^{***}$ | BAC | 0.8827 | 0.0048 | 0.5876 | 0.0405 | -7.24$^{***}$ |
| BAC | 0.8737 | 0.0064 | 0.7906 | 0.0314 | -2.59$^{***}$ | C | 0.8845 | 0.0051 | 0.4927 | 0.0584 | -6.68$^{***}$ |
| C | 0.8859 | 0.0056 | 0.7923 | 0.0318 | -2.90$^{***}$ | JPM | 0.8976 | 0.0042 | 0.4554 | 0.0592 | -7.45$^{***}$ |
| JPM | 0.8845 | 0.0058 | 0.8047 | 0.0317 | -2.48$^{***}$ | MS | 0.9315 | 0.0026 | 0.4334 | 0.0777 | -6.40$^{***}$ |
| MS | 0.9330 | 0.0026 | 0.8096 | 0.0295 | -4.16$^{***}$ | AIG | 0.8024 | 0.0109 | 0.6321 | 0.0441 | -3.75$^{***}$ |
| AIG | 0.8174 | 0.0106 | 0.6899 | 0.0511 | -2.44$^{***}$ | | | | | | |
| **WAMUto** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | **MERto** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
| MER | 0.8036 | 0.0114 | 0.4433 | 0.0824 | -4.33$^{***}$ | WFC | 0.8138 | 0.0088 | 0.5824 | 0.0552 | -4.14$^{***}$ |
| WB | 0.8348 | 0.0100 | 0.4860 | 0.0831 | -4.16$^{***}$ | GS | 0.8985 | 0.0045 | 0.5044 | 0.1022 | -3.85$^{***}$ |
| WFC | 0.8363 | 0.0089 | 0.3514 | 0.0941 | -5.13$^{***}$ | BAC | 0.8219 | 0.0072 | 0.7418 | 0.0228 | -3.35$^{***}$ |
| GS | 0.7631 | 0.0128 | 0.3496 | 0.0816 | -5.01$^{***}$ | C | 0.8470 | 0.0073 | 0.7063 | 0.0449 | -3.09$^{***}$ |
| BAC | 0.8100 | 0.0096 | 0.3937 | 0.0772 | -5.35$^{***}$ | JPM | 0.8581 | 0.0067 | 0.4618 | 0.0900 | -4.39$^{***}$ |
| C | 0.8006 | 0.0119 | 0.3996 | 0.0898 | -4.42$^{***}$ | MS | 0.8892 | 0.0048 | 0.6768 | 0.0418 | -5.04$^{***}$ |
| JPM | 0.8030 | 0.0123 | 0.1246 | 0.1184 | -5.70$^{***}$ | AIG | 0.6713 | 0.0137 | 0.5711 | 0.0285 | -3.16$^{***}$ |
| MS | 0.7600 | 0.0140 | 0.4090 | 0.0828 | -4.18$^{***}$ | | | | | | |
| AIG | 0.7229 | 0.0173 | 0.4624 | 0.0779 | -3.26$^{***}$ | | | | | | |
| **WB to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | | | | | | |
| WFC | 0.9553 | 0.0018 | 0.7232 | 0.0484 | -4.79$^{***}$ | | | | | | |
| GS | 0.9006 | 0.0056 | 0.4143 | 0.1055 | -4.60$^{***}$ | | | | | | |
| BAC | 0.9516 | 0.0021 | 0.7122 | 0.0520 | -4.60$^{***}$ | | | | | | |
| C | 0.9270 | 0.0037 | 0.6744 | 0.0585 | -4.31$^{***}$ | | | | | | |
| JPM | 0.9280 | 0.0036 | 0.5673 | 0.0810 | -4.45$^{***}$ | | | | | | |
| MS | 0.9075 | 0.0049 | 0.5067 | 0.0795 | -5.04$^{***}$ | | | | | | |
| AIG | 0.8797 | 0.0062 | 0.5620 | 0.0609 | -5.19$^{***}$ | | | | | | |

Notes: Flight to quality from five troubled banks to the remaining safe banks is reported. The main regression model assumes that the local correlation estimators are normally distributed even though the underlying time series is not normally distributed. The estimated correlation coefficients of the median and the lower 2.5% quantile along with their estimated standard deviations are reported. The one sided t-test statistics for the statistical difference between the median and the lower quantile correlation coefficients are reported in the last column. $^{**}$, $^{***}$ represent 5% and 1% statistical significance, respectively (The critical values of the test statistic are -1.65 and -2.33 for 5% and 1% significance levels, respectively).

Even though the distributions of the local correlation estimators obtained from running the bootstrapping procedure 1,000 times are indeed approximately normal, we also consider the possibility that there may be serial correlations in the residuals. Therefore, a vector autoregression (VAR) model with orders ranging from 1 to 5 days is used to take into account any potential serial dependencies between the troubled and safer bank returns. The results of the VAR regression with order 1 are reported in Table 3 for contemporaneous flight to quality.[3]

**Table 3. Flight to Quality: VAR(1) Distributed Local Correlation Estimators**

| **BSC to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | **LEHto** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| LEH | 0.9298 | 0.0026 | 0.7816 | 0.0228 | -6.47*** | WAMU | 0.8089 | 0.0095 | 0.5004 | 0.0537 | -5.65*** |
| WAMU | 0.7626 | 0.0137 | 0.6578 | 0.0503 | -2.01** | MER | 0.9224 | 0.0028 | 0.6591 | 0.0430 | -6.12*** |
| MER | 0.9204 | 0.0034 | 0.8521 | 0.0239 | -2.83*** | WB | 0.8516 | 0.0068 | 0.6491 | 0.0355 | -5.61*** |
| WB | 0.8455 | 0.0083 | 0.8310 | 0.0280 | -0.50 | WFC | 0.8627 | 0.0059 | 0.4856 | 0.0509 | -7.36*** |
| WFC | 0.8354 | 0.0090 | 0.8258 | 0.0279 | -0.33 | GS | 0.9453 | 0.0019 | 0.3841 | 0.0909 | -6.18*** |
| GS | 0.9323 | 0.0027 | 0.7946 | 0.0364 | -3.77*** | BAC | 0.8753 | 0.0053 | 0.5847 | 0.0427 | -6.76*** |
| BAC | 0.8478 | 0.0082 | 0.8278 | 0.0279 | -0.69 | C | 0.8904 | 0.0048 | 0.4526 | 0.0658 | -6.63*** |
| C | 0.8606 | 0.0072 | 0.8310 | 0.0261 | -1.09 | JPM | 0.8892 | 0.0048 | 0.4595 | 0.0659 | -6.51*** |
| JPM | 0.8518 | 0.0080 | 0.8404 | 0.0254 | -0.43 | MS | 0.9277 | 0.0028 | 0.3741 | 0.0885 | -6.25*** |
| MS | 0.9180 | 0.0034 | 0.8304 | 0.0280 | -3.10*** | AIG | 0.7872 | 0.0114 | 0.5191 | 0.0557 | -4.71*** |
| AIG | 0.7940 | 0.0122 | 0.7207 | 0.0498 | -1.43* | | | | | | |
| **WAMU** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | **MERto** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
| MER | 0.8095 | 0.0112 | 0.4400 | 0.0849 | -4.32*** | WFC | 0.8123 | 0.0088 | 0.5995 | 0.0511 | -4.10*** |
| WB | 0.8170 | 0.0103 | 0.5046 | 0.0741 | -4.18*** | GS | 0.8989 | 0.0043 | 0.4854 | 0.0907 | -4.55*** |
| WFC | 0.8371 | 0.0091 | 0.3415 | 0.0989 | -4.99*** | BAC | 0.8116 | 0.0082 | 0.7490 | 0.0249 | -2.38*** |
| GS | 0.7631 | 0.0139 | 0.2311 | 0.1088 | -4.85*** | C | 0.8371 | 0.0071 | 0.6791 | 0.0370 | -4.19*** |
| BAC | 0.8113 | 0.0105 | 0.3440 | 0.0913 | -5.09*** | JPM | 0.8606 | 0.0066 | 0.4554 | 0.0911 | -4.43*** |
| C | 0.7983 | 0.0124 | 0.3399 | 0.1029 | -4.42*** | MS | 0.8831 | 0.0052 | 0.6638 | 0.0471 | -4.62*** |
| JPM | 0.8030 | 0.0121 | 0.0858 | 0.1196 | -5.97*** | AIG | 0.6412 | 0.0172 | 0.5848 | 0.0399 | -1.30* |
| MS | 0.7508 | 0.0150 | 0.3692 | 0.0935 | -4.03*** | | | | | | |
| AIG | 0.7322 | 0.0140 | 0.3105 | 0.0701 | -5.90*** | | | | | | |
| **WB to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | | | | | | |
| WFC | 0.9552 | 0.0018 | 0.6205 | 0.0684 | -4.89*** | | | | | | |
| GS | 0.8760 | 0.0074 | 0.3963 | 0.0936 | -5.11*** | | | | | | |
| BAC | 0.9404 | 0.0028 | 0.7560 | 0.0370 | -4.96*** | | | | | | |
| C | 0.9309 | 0.0035 | 0.5641 | 0.0796 | -4.61*** | | | | | | |
| JPM | 0.9182 | 0.0043 | 0.4535 | 0.0945 | -4.91*** | | | | | | |
| MS | 0.8848 | 0.0067 | 0.5113 | 0.0737 | -5.05*** | | | | | | |
| AIG | 0.8670 | 0.0069 | 0.4134 | 0.0687 | -6.57*** | | | | | | |

Notes: Flight to quality from five troubled banks to the remaining safe banks is reported. Vector autoregression (VAR) model with order 1 is used to take into account any potential serial dependencies in regression residuals. *, **, *** represent 10%, 5%, and 1% statistical significance, respectively.

We find consistent evidence of flight to quality from troubled banks to safer banks at the 1% significance level in most cases. For example, evidence of contemporaneous flight to quality from Lehman, Washington Mutual, and Wachovia Bank to the other banks is significant at 1%. This conclusion is largely valid for Merrill Lynch (with the significance level of 10% to AIG). As for Bear-Stearns, the flight to quality is seen with the majority (7 out of 11) of the banks.

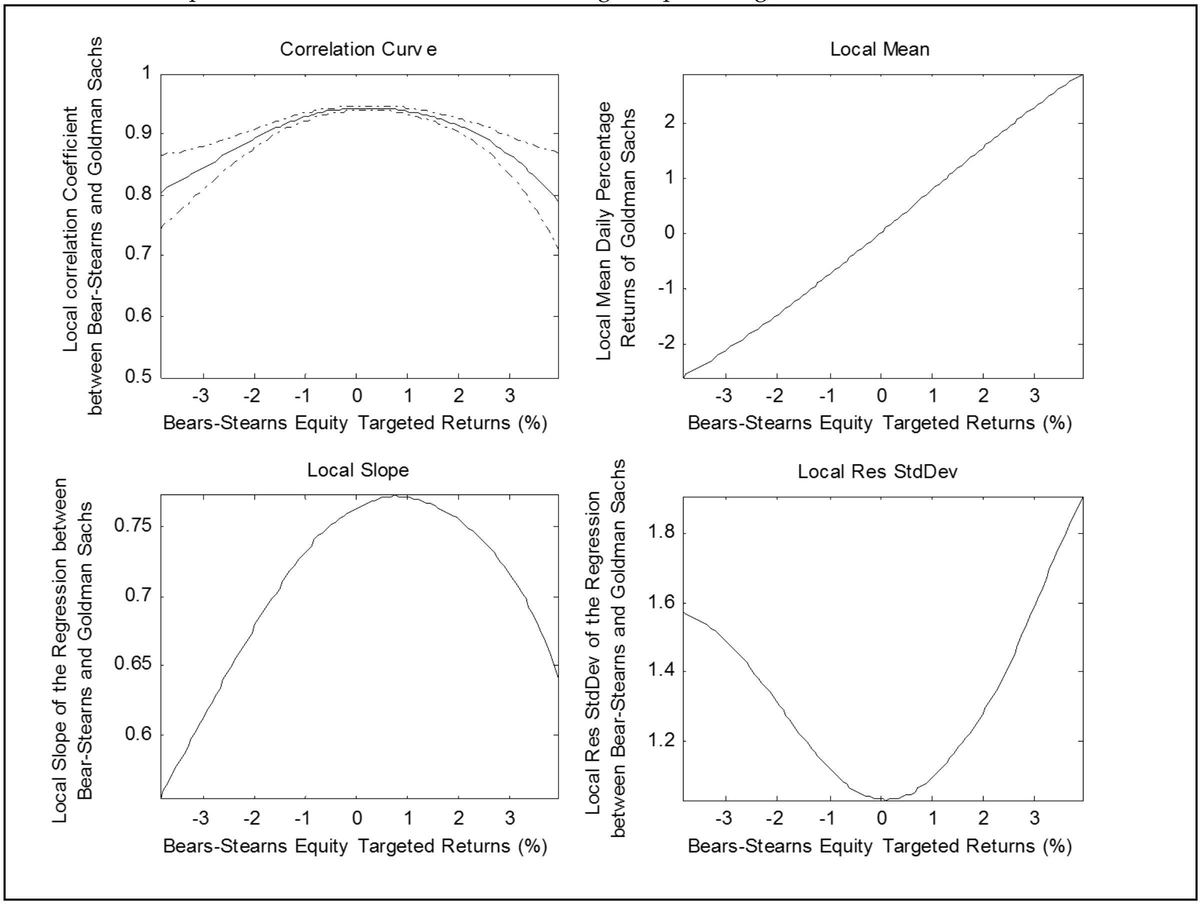
The analysis thus far examines flight to quality using returns with dividends. For robustness, we examine the local correlation relationships using returns excluding dividends. We again obtained clear evidence of flight to quality at the 1% significance level. For Bear-Stearns, Lehman, Washington Mutual, Wachovia Bank, and Merrill Lynch, the median local correlation is consistently above the local correlation coefficient associated with the extreme loss tail, indicating that when a troubled bank suffers losses, investors shift their holdings towards safer banks. Therefore, during bad times, local correlation is lower between a troubled and a safe bank compared to the median local correlation

[3] Results from VAR models with higher orders are similar to the results from the VAR(1) model.

corresponding to normal times.[4]

**Figure I. Local Statistics of the Goldman Sachs vs. Bear-Stearns Returns**

The correlation, local mean, slope and residual standard deviation values for the contemporaneous Goldman Sachs returns are plotted as a function of those of the targeted percentage returns of Bear-Stearns.




The analytical results of flight to quality can be graphed for interpretation similar to Bradley and Taqqu (2005a, 2005b). We plot the estimates from Table 2. Local correlation values obtained from Bear-Stearns (BSC) to Goldman Sachs (GS) are shown in Figure I. The local correlation $\rho(z)$, local mean $m'(z)$, slope $\beta(z)$, and residual standard deviation $\sigma(z)$ values are plotted for Bear-Stearns. The 95 percent confidence intervals around the correlation curve are also shown. As the top left plot indicates, the returns between the troubled bank, Bear-Stearns, and the safe bank, Goldman Sachs, have varying degrees of conditional dependence. The local correlations between BSC and GS decrease, and converge to 0.8036. As one approaches the median quantiles, the local correlation estimate goes up, and converges to 0.9430, which is the local correlation estimate associated with the median quantile of the return distribution. As such, the use of unconditional correlation can be misleading for investors.[5]

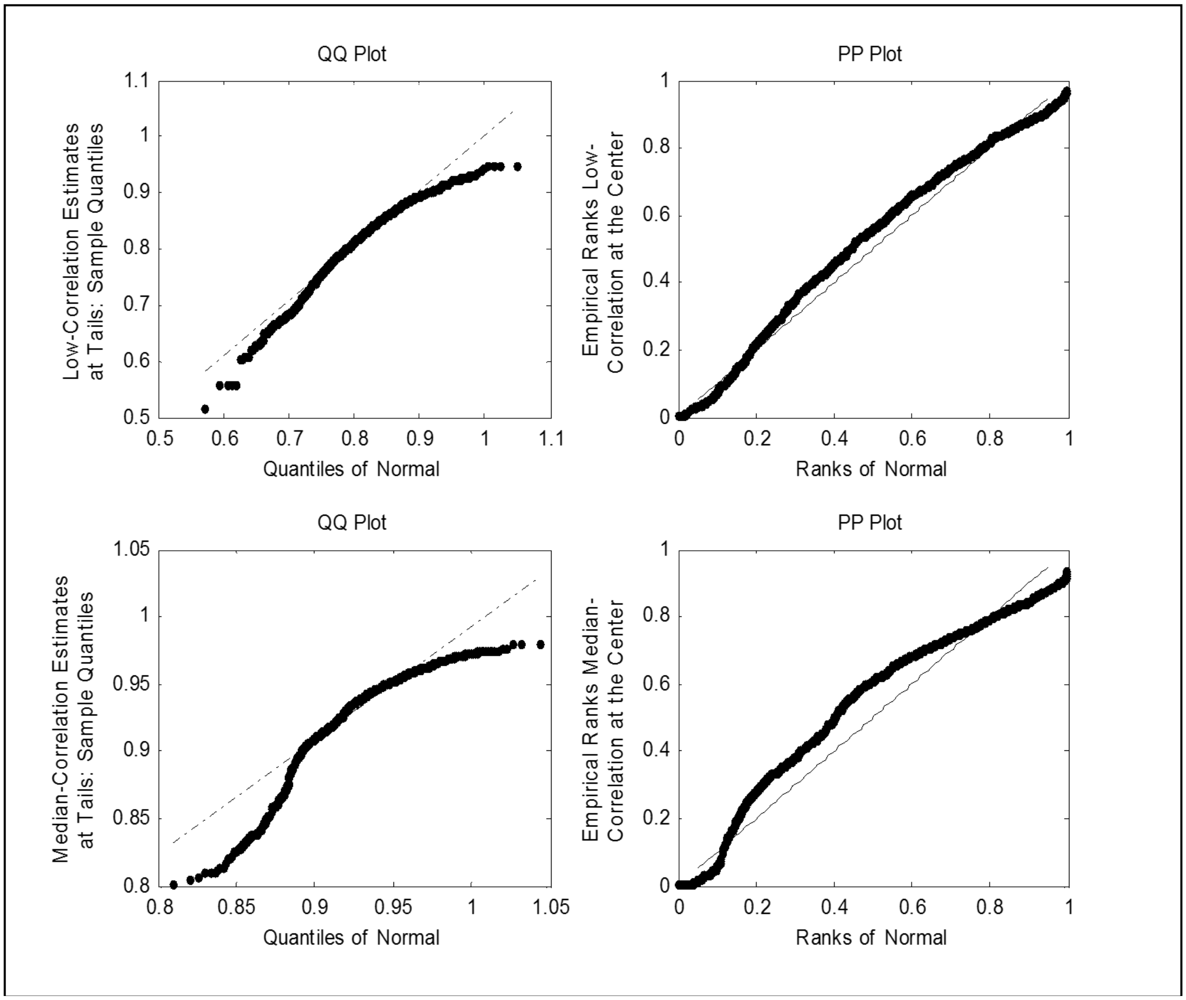
The bottom left figure is the slope coefficient of the local correlation estimates. As BSC returns diverge from the median, the local slope continues to decline. The local mean values of the GS estimates are provided in the top right panel. Finally, the bottom right figure provides the local residual standard deviations, indicating that the residual variance is a function of the covariate.

[4] These results are available upon request.

[5] We obtain similar diagrams in all flight to quality investigations; namely, the correlation between troubled and other bank returns decrease as troubled bank returns decrease further from the median.

**Figure II. Bootstrapped Distribution QQ and PP Plots of Local Correlation between Bear-Stearns and Goldman Sachs**

The Quantile-Quantile (QQ) and Probability-Probability (PP) plots for the distribution of $\hat{\rho}(z_L)$ and $\hat{\rho}(z_M)$, the local correlation between S&P 500 Index Futures and 10-year Treasury Bond Futures, versus the normal distribution obtained from 1000 Bootstrap samples are presented. The top two graphs are for $\hat{\rho}(z_L)$ and the lower two graphs are for $\hat{\rho}(z_M)$.




It is helpful to use graphic techniques for determining whether VAR should be used to remove serial dependencies of bank returns. Knowing that the quantiles of return series tend typically to bunch up in the center of a distribution and spread out in the tails, the Quantile-Quantile (QQ) plots are used for checking the goodness of fit between the correlation coefficient distribution and the normal distribution in the tails, and the Probability-Probability (PP) plots for checking that in the center of the distribution (Bradley and Taqqu, 2005b).

Figure II presents the Quantile-Quantile (QQ) and Probability-Probability (PP) plots of the local correlation estimates between BSC and GS, versus the normal distribution obtained from 1,000 Bootstrap samples. The top two graphs are for the lower-quantile estimates, and the bottom two graphs are for the median estimates. There are significant deviations from the straight lines, especially in the QQ plots, indicating that removal of serial dependencies is appropriate and the results of the VAR(1) model reported in Table 3 are important.

### 4.2. Flight to Quality based on Abnormal Returns

The results and conclusions thus far focus on raw returns. To strengthen our conclusions and for robustness we examine market-adjusted stock returns; i.e., the difference between raw returns and market or banking sector returns. We use both the value-weighted market returns and equally-weighted market returns.

Table 4 presents the results of the local correlation analysis between the troubled bank market-adjusted returns and the contemporaneous market-adjusted returns of other banks. Panel A uses value-weighted market returns, while Panel B uses equally-weighted market returns. We see consistent evidence of flight to quality similar to the results based on raw returns. The local correlation coefficient at the extreme-loss tail is consistently lower than the median local correlation. This represents the impulse response of market participants when stock price declines at the extreme-loss tail of troubled banks. Market participants seem to shift their stock holdings to other banks on a contemporaneous basis when stocks of troubled banks experience large declines. The statistical significance of the results is slightly higher in Panel B with the equally-weighted market returns.

**Table 4. Flight to Quality with Market Adjusted Returns**

| **Panel A. Abnormal returns based on Value-Weighted market returns** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **BSC to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | **LEH to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
| LEH | 0.9049 | 0.0057 | 0.7440 | 0.0633 | -2.53*** | WAMU | 0.6018 | 0.0293 | 0.4300 | 0.0679 | -2.32*** |
| WAMU | 0.5907 | 0.0354 | 0.5303 | 0.0836 | -0.67 | MER | 0.8654 | 0.0058 | 0.6109 | 0.0284 | -8.78*** |
| MER | 0.8544 | 0.0097 | 0.7450 | 0.0444 | -2.41*** | WB | 0.7423 | 0.0147 | 0.5006 | 0.0395 | -5.74*** |
| WB | 0.5494 | 0.0385 | 0.3840 | 0.1056 | -1.47* | WFC | 0.5194 | 0.0364 | 0.3867 | 0.0761 | -1.57* |
| WFC | 0.4957 | 0.0451 | 0.4229 | 0.1068 | -0.63 | GS | 0.8842 | 0.0059 | 0.5285 | 0.0589 | -6.01*** |
| GS | 0.8564 | 0.0090 | 0.6182 | 0.0648 | -3.64*** | BAC | 0.6516 | 0.0237 | 0.4786 | 0.0506 | -3.10*** |
| BAC | 0.5149 | 0.0420 | 0.5081 | 0.0864 | -0.07 | C | 0.6727 | 0.0211 | 0.4213 | 0.0504 | -4.60*** |
| C | 0.5618 | 0.0374 | 0.5657 | 0.0752 | 0.05 | JPM | 0.7004 | 0.0186 | 0.4241 | 0.0483 | -5.34*** |
| JPM | 0.5875 | 0.0354 | 0.5181 | 0.0846 | -0.76 | MS | 0.8488 | 0.0085 | 0.4469 | 0.0664 | -6.01*** |
| MS | 0.8132 | 0.0126 | 0.5516 | 0.0747 | -3.45*** | AIG | 0.4666 | 0.0397 | 0.5382 | 0.0542 | 1.07 |
| AIG | 0.3381 | 0.0548 | 0.2760 | 0.1187 | -0.47 | | | | | | |
| **WAMU to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | **MER to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
| MER | 0.5860 | 0.0234 | 0.4221 | 0.0529 | -2.83*** | WFC | 0.4539 | 0.0294 | 0.2258 | 0.0684 | -3.06*** |
| WB | 0.7111 | 0.0209 | 0.3793 | 0.0830 | -3.88*** | GS | 0.7558 | 0.0151 | 0.1975 | 0.1191 | -4.65*** |
| WFC | 0.7052 | 0.0196 | 0.2371 | 0.0871 | -5.24*** | BAC | 0.5903 | 0.0457 | 0.4996 | 0.0294 | -1.67** |
| GS | 0.3583 | 0.0456 | 0.4039 | 0.0735 | 0.53 | C | 0.6132 | 0.0251 | 0.5799 | 0.0593 | -0.52 |
| BAC | 0.6946 | 0.0159 | 0.2905 | 0.0556 | -6.99*** | JPM | 0.6551 | 0.0215 | 0.2410 | 0.0967 | -4.18*** |
| C | 0.5782 | 0.0225 | 0.3392 | 0.0494 | -4.40*** | MS | 0.7396 | 0.0153 | 0.3004 | 0.0763 | -5.64*** |
| JPM | 0.4114 | 0.0382 | 0.3063 | 0.0755 | -1.24 | AIG | 0.5030 | 0.0491 | 0.3481 | 0.0347 | -2.58*** |
| MS | 0.3927 | 0.0666 | 0.3375 | 0.0414 | -0.70 | **WB to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
| AIG | 0.4407 | 0.0444 | 0.2600 | 0.0992 | -1.66** | WFC | 0.9098 | 0.0059 | 0.5919 | 0.0722 | -4.39*** |
| | | | | | | GS | 0.5800 | 0.0406 | 0.2701 | 0.1028 | -2.80*** |
| | | | | | | BAC | 0.8954 | 0.0075 | 0.5977 | 0.0727 | -4.07*** |
| | | | | | | C | 0.8252 | 0.0148 | 0.5342 | 0.0833 | -3.44*** |
| | | | | | | JPM | 0.7227 | 0.0266 | 0.4883 | 0.0878 | -2.56*** |
| | | | | | | MS | 0.5796 | 0.0404 | 0.3805 | 0.0690 | -2.49*** |
| | | | | | | AIG | 0.7365 | 0.0198 | 0.4944 | 0.0603 | -3.82*** |

**Table 4. Flight to Quality with Market Adjusted Returns**

| Panel B. Abnormal returns based on Equally-Weighted market returns | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **BSC to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | **LEH to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
| LEH | 0.9229 | 0.0039 | 0.7813 | 0.0458 | -3.08*** | WAMU | 0.6750 | 0.0215 | 0.4290 | 0.0605 | -3.83*** |
| WAMU | 0.6598 | 0.0260 | 0.5639 | 0.0729 | -1.24 | MER | 0.8923 | 0.0045 | 0.6321 | 0.0312 | -8.25*** |
| MER | 0.8915 | 0.0061 | 0.7784 | 0.0375 | -2.98*** | WB | 0.7969 | 0.0106 | 0.5220 | 0.0401 | -6.63*** |
| WB | 0.7235 | 0.0201 | 0.4684 | 0.0891 | -2.79*** | WFC | 0.6883 | 0.0210 | 0.3850 | 0.0700 | -4.15*** |
| WFC | 0.6886 | 0.0231 | 0.4833 | 0.0860 | -2.31** | GS | 0.9059 | 0.0043 | 0.4915 | 0.0630 | -6.56*** |
| GS | 0.8969 | 0.0055 | 0.6224 | 0.0662 | -4.14*** | BAC | 0.7578 | 0.0141 | 0.4443 | 0.0528 | -5.74*** |
| BAC | 0.7109 | 0.0210 | 0.5568 | 0.0732 | -2.02** | C | 0.7759 | 0.0128 | 0.4216 | 0.0549 | -6.29*** |
| C | 0.7519 | 0.0178 | 0.5806 | 0.0708 | -2.35*** | JPM | 0.7934 | 0.0112 | 0.3943 | 0.0545 | -7.17*** |
| JPM | 0.7599 | 0.0177 | 0.6212 | 0.0685 | -1.96** | MS | 0.8880 | 0.0054 | 0.4352 | 0.0661 | -6.83*** |
| MS | 0.8759 | 0.0070 | 0.5921 | 0.0695 | -4.06*** | AIG | 0.6344 | 0.0251 | 0.5039 | 0.0550 | -2.16** |
| AIG | 0.6048 | 0.0311 | 0.3489 | 0.1072 | -2.29** | | | | | | |
| **WAMU to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | **MER to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
| MER | 0.6281 | 0.0243 | 0.4680 | 0.0643 | -2.33*** | WFC | 0.5968 | 0.0233 | 0.2879 | 0.0773 | -3.82*** |
| WB | 0.7603 | 0.0165 | 0.3964 | 0.0831 | -4.30*** | GS | 0.8100 | 0.0108 | 0.1979 | 0.1177 | -5.18*** |
| WFC | 0.7586 | 0.0158 | 0.2059 | 0.0929 | -5.87*** | BAC | 0.6485 | 0.0190 | 0.6363 | 0.0374 | -0.29 |
| GS | 0.5297 | 0.0288 | 0.3511 | 0.0687 | -2.40*** | C | 0.6393 | 0.0226 | 0.6370 | 0.0478 | -0.04 |
| BAC | 0.7171 | 0.0149 | 0.2952 | 0.0630 | -6.52*** | JPM | 0.7338 | 0.0160 | 0.3299 | 0.0935 | -4.26*** |
| C | 0.6453 | 0.0235 | 0.4163 | 0.0709 | -3.07*** | MS | 0.7890 | 0.0115 | 0.3820 | 0.0743 | -5.41*** |
| JPM | 0.5669 | 0.0309 | 0.2058 | 0.0906 | -3.77*** | AIG | 0.5713 | 0.0512 | 0.3127 | 0.0402 | -3.97*** |
| MS | 0.5392 | 0.0253 | 0.3309 | 0.0566 | -3.36*** | **WB to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
| AIG | 0.5907 | 0.0309 | 0.2616 | 0.0921 | -3.39*** | WFC | 0.9260 | 0.0042 | 0.6100 | 0.0724 | -4.36*** |
| | | | | | | GS | 0.7492 | 0.0210 | 0.2614 | 0.1099 | -4.36*** |
| | | | | | | BAC | 0.9258 | 0.0043 | 0.5608 | 0.0877 | -4.16*** |
| | | | | | | C | 0.8675 | 0.0097 | 0.4805 | 0.0997 | -3.86*** |
| | | | | | | JPM | 0.8363 | 0.0127 | 0.4241 | 0.1039 | -3.94*** |
| | | | | | | MS | 0.7491 | 0.0211 | 0.4966 | 0.0565 | -4.19*** |
| | | | | | | AIG | 0.8092 | 0.0125 | 0.5121 | 0.0624 | -4.66*** |

Notes: Flight to Quality from the five troubled bank market adjusted returns to contemporaneous market adjusted returns of the remaining banks is reported. Panel A utilizes value-weighted market returns. Panel B utilizes equally-weighted market returns. *, **, *** represent 10%, 5%, and 1% statistical significance.

Finally, in Table 5 we use banking sector index returns to compute the adjusted returns and investigate flight to quality. The bank index returns are calculated from the PHLX KBW Bank Sector Index, a capitalization-weighted index formed from 24 geographically diverse stocks representing national money center banks and leading regional institutions. The index is based on one-tenth the value of the value of the Keefe, Bruyette & Woods Index (KBW). Founded in 1962, Keefe, Bruyette & Woods follow more than 200 commercial banking and thrift industries on a daily basis, and have long been recognized by banking industry experts. We examine the abnormal returns for the twelve banks by utilizing this banking sector return index rather than the total market return.

Even though the adjusted returns are calculated in a different manner, previous conclusions still hold. Results clearly depict contemporaneous flight to quality from troubled banks to others.

**5. Conclusion**

When banks are viewed as heterogeneous agents, it is not surprising to learn that reactions to changes in market conditions vary among institutions. This study uses local correlation analysis to detect the occurring sequence of flight to quality The heterogeneous response to changing market conditions suggests that the implied assumption of homogeneous agents in financial analysis has its limitations.

**Table 5. Flight to Quality with Banking Sector Adjusted Returns**

| Flight to Quality | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **BSC to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | **LEH to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
| LEH | 0.8935 | 0.0072 | 0.3706 | 0.2038 | -2.56*** | WAMU | 0.2393 | 0.0525 | 0.2749 | 0.0969 | 0.32 |
| WAMU | 0.3317 | 0.1168 | 0.2527 | 0.0651 | -0.59 | MER | 0.7674 | 0.0143 | 0.5226 | 0.0590 | -4.03*** |
| MER | 0.8277 | 0.0128 | 0.6034 | 0.0781 | -2.83*** | WB | 0.3359 | 0.0333 | 0.2632 | 0.0429 | -1.34* |
| WB | 0.1067 | 0.0699 | 0.0990 | 0.1257 | -0.05 | WFC | -0.2645 | 0.0490 | -0.2503 | 0.0869 | 0.14 |
| WFC | 0.1541 | 0.1249 | 0.0618 | 0.0708 | -0.64 | GS | 0.7925 | 0.0129 | -0.0537 | 0.1068 | -7.86*** |
| GS | 0.8554 | 0.0099 | 0.6304 | 0.0589 | -3.77*** | BAC | -0.0805 | 0.0437 | -0.1920 | 0.0547 | -1.59* |
| BAC | 0.1843 | 0.0617 | 0.1889 | 0.1058 | 0.04 | C | 0.2115 | 0.0420 | 0.1254 | 0.0503 | -1.31* |
| C | 0.0335 | 0.0708 | -0.0749 | 0.1242 | -0.76 | JPM | 0.2923 | 0.0446 | -0.0114 | 0.0770 | -3.41*** |
| JPM | 0.7997 | 0.0151 | 0.4157 | 0.0916 | -4.13*** | MS | 0.7338 | 0.0181 | 0.0322 | 0.1098 | -6.31*** |
| MS | 0.1697 | 0.0608 | 0.0585 | 0.1158 | -0.85 | AIG | 0.2381 | 0.0498 | 0.0404 | 0.1023 | -1.74** |
| AIG | 0.1565 | 0.0533 | 0.0525 | 0.1097 | -0.85 | | | | | | |
| **WAMU to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ | **MER to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
| MER | 0.2194 | 0.0415 | 0.0591 | 0.1207 | -1.26 | WFC | -0.1650 | 0.0344 | -0.2775 | 0.0690 | -1.46* |
| WB | 0.3664 | 0.0488 | 0.1184 | 0.1412 | -1.66** | GS | 0.5750 | 0.0226 | 0.1209 | 0.0991 | -4.47*** |
| WFC | 0.1737 | 0.0523 | -0.0999 | 0.1099 | -2.25** | BAC | 0.0830 | 0.0426 | -0.0628 | 0.1177 | -1.17 |
| GS | 0.0906 | 0.0606 | -0.0699 | 0.1464 | -1.01 | C | 0.2703 | 0.0349 | 0.1163 | 0.1358 | -1.10 |
| BAC | 0.1053 | 0.0574 | -0.1209 | 0.1325 | -1.57* | JPM | 0.2431 | 0.0347 | 0.0714 | 0.0836 | -1.90** |
| C | 0.0650 | 0.0469 | -0.0619 | 0.1307 | -0.91 | MS | 0.5453 | 0.0246 | 0.3875 | 0.0847 | -1.79** |
| JPM | -0.0334 | 0.0483 | -0.1446 | 0.0967 | -1.04 | AIG | -0.0176 | 0.0388 | -0.1734 | 0.0853 | -1.66** |
| MS | -0.0284 | 0.0518 | -0.2327 | 0.1413 | -1.36* | **WB to** | $\hat{\rho}(z_M)$ | $\hat{\sigma}_{\hat{\rho}(z_M)}$ | $\hat{\rho}(z_L)$ | $\hat{\sigma}_{\hat{\rho}(z_L)}$ | $\hat{T}$ |
| AIG | 0.2897 | 0.0520 | 0.0378 | 0.1384 | -1.70** | WFC | 0.4714 | 0.0469 | 0.1268 | 0.0921 | -3.33*** |
| | | | | | | GS | 0.1216 | 0.0527 | -0.0033 | 0.1253 | -0.92 |
| | | | | | | BAC | 0.1005 | 0.0485 | -0.0547 | 0.0897 | -1.52* |
| | | | | | | C | 0.0659 | 0.0686 | -0.1661 | 0.1424 | -1.47* |
| | | | | | | JPM | -0.3108 | 0.0529 | -0.2689 | 0.0614 | 0.52 |
| | | | | | | MS | 0.2479 | 0.0488 | 0.0645 | 0.0769 | -2.01** |
| | | | | | | AIG | 0.3500 | 0.0535 | 0.1893 | 0.0804 | -1.66** |

Notes: Flight to quality from bank sector adjusted returns of the five troubled banks to those of the remaining banks is reported. *, **, *** represent 10%, 5%, and 1% statistical significance.

The unfolding of flight to quality over time in the banking market points out the inadequacy of static analysis. When financial activities of heterogeneous agents are viewed as an evolving process, our study captures flight to quality through the application of local correlation analysis. Our findings have important implications for risk management given that various diversification strategies are likely to be in need of adjustment during periods of market turmoil. While the traditional Pearson correlation calculation captures the general overall linear association, local correlation analysis captures changes in the associations in response to changing market conditions.

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