To investigate dynamic relations between stock returns and equity mutual fund flows at the macro level, we combine information from the stock market with information from bond and money markets in a system method. The empirical evidence from SURECM and Granger causality tests indicates that there seems to be a positive long-run relationship between stock returns and fund flows, and the stock returns may lead fund flows. Furthermore, if there is a deviation from long-run equilibrium, equity mutual fund flows are weakly exogenous and the security returns seem to force the deviation to go toward the long-run equilibrium. Thus, investors tend to move their money to the securities that yield higher returns, stock returns are likely to lead fund flows and the most important element explaining equity mutual fund flows seems to be security performance in the US market.
1. Introduction

Do aggregate mutual fund flows into and out of the market affect stock returns? This paper studies the dynamics between stock returns and aggregate equity mutual fund flows using a system method in the US financial market. There is an intense debate over whether mutual fund flows have any relevance at all to the market’s direction.\(^1\) Is the torrent of money pouring into mutual funds driving the market upward, or is the strong stock market driving investors to shovel millions of dollars into funds each month? And how much do mutual fund flows really matter to stock market movement in the first place? The degree to which prior stock market returns influence investor demand for mutual fund shares and to what extent this demand drives returns have important implications for the stability of the U.S. stock market. Substantial efforts have been made to detect the relationships explained by security returns and mutual fund flows. However, empirical evidence between the security returns and the mutual fund flows has not been satisfied.

In analyzing the relations between security returns and mutual fund flows, the studies have mainly employed two different approaches. One is a micro approach and the other is a macro approach. The former focuses attention on how mutual funds flows are analyzed on an individual basis and finds that investors tend to move cash into the funds that had the highest returns in the preceding years.\(^2\) The macro approach, on the other hand, is important in explaining the relationship between security returns and mutual fund flows.\(^3\) It is different from the micro approach in that the macro approach

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\(^2\) See Ippolito (1992), Sirri and Tufano (1993), and Hendricks, Patel, and Zeckhauser (1993) for details.

\(^3\) See Warther (1995) for details.
focuses on large scale of movements of money into and out of the market without regard to which fund it goes into or comes from. Hence, the research at the macro level has centered on the relationship between security returns and aggregate mutual fund flows.

The current literature on the relationship indicates that in general there exists high correlation between aggregate mutual fund flows and security returns. Further, the theoretical approaches such as the price pressure theory, the information revelation hypothesis, and investor sentiment also explain the positive correlation between aggregate mutual fund flows and security returns. However, it is not clear whether there exist positive significant correlations between aggregate mutual fund flows and security returns, and whether the security markets are driven by mutual fund inflows and outflows due to the following reasons. First, the above mentioned literature use logged differenced or normalized data, which removes the unit root or permanent component of the data, and therefore avoids the complications related to unit roots and spurious regressions. As shown by Stock and Watson (1988), however, since business cycle activity comprises both temporary and permanent components, which are often related with each other, the removal of the permanent component removes valuable long term information concerning the evolvement of short-term movements. Second, despite the considerable dispute, finance theory gives no clear answer to the question of whether changes in mutual fund flows can cause changes in asset prices. Furthermore, as the theory predicts, even though fund flows and security returns have a high positive correlation, it does not necessarily imply that the former causes the latter and vice versa because there might be

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other possible reasons for the causal relationship.\textsuperscript{5}

This paper aims to enhance the understanding of the dynamics in security markets by analyzing the interactions between security returns and aggregate mutual fund flows using a system method. More specifically, in order to investigate short run, long run, and causal relationships between stock returns and cash flows, we combine information from stock market with information from bond and money markets in the system method. In general, the security markets such as stock market, bond market, and money market are closely related with one another so that those who have accounts in security markets tend to move their funds without any difficulty to the accounts with higher returns. When markets have such a close relationship with one another, the system method is more efficient than a single equation method because the system method combines information from the stock market as well as the other markets such as bond and money markets.

To examine the short and long run dynamic relationship between security returns and mutual fund flows, we employ econometric procedures that are more efficient than ordinary methods. Augmented Dickey-Fuller (SURADF) and KPSS (1992) tests are used for unit root,\textsuperscript{6} and Park’s (1992) Canonical Cointegration Regression (CCR) method for cointegration is employed. Furthermore, for short run dynamics this study employs seemingly unrelated regression error correction model (SURECM). More specifically, in order to account for cross equation correlations we present a seemingly unrelated regression methodology and also make use of information in the variance-covariance matrix of residuals to improve the efficiency of the statistical estimates. Finally, in order

\textsuperscript{5} For details, see Potter and Schneeweis (1998), Remolona, Kleiman, and Gruenstein (1997), and Fortune (1998).
\textsuperscript{6} See Appendix for details. For the ADF test, the null hypothesis is non-stationarity. On the other hand, for the KPSS tests, the null is stationary in levels.
to check the existence of any causal relationship between the two variables, we employ Granger (1969) causality tests.

This study makes a unique contribution to the security return-fund flow literature as the substantive study that documents the short and long run relations by capturing the dynamic linkages between security returns and equity mutual fund flows at the macro level using a system approach based on a seemingly unrelated regression methodology. The empirical results in this paper show that unlike Warther (1995) there exist large and positive correlations between security returns, and negative correlations between cash flows in stock, bond, and money markets.\textsuperscript{7} Second, there seems to be a long-run relationship between security returns and cash flows in stock and money markets. Third, security returns seems to contemporaneously lead cash flows in the market with the exception of money market case in which a feedback contemporaneous relation exists between money market returns and cash flows.\textsuperscript{8}

Our empirical results are not likely to support the popular notion that markets are driven by mutual fund flows. According to our results, investors tend to move their money to the securities that yield higher returns, implying that stocks and bonds are likely to be substitutes and previous changes in stock returns might cause changes in cash flows in the same direction because of positive short-term effect. However, it is likely that the same is not true for cash flows. Taken together, mutual fund flows do not seem to be fundamental factors affecting security returns. Furthermore, the most significant factor explaining mutual fund flows appears to be measures of security performance in the U.S. financial market.

\textsuperscript{7} For details, see Warther (1995).
\textsuperscript{8} According to Grinblatt, Titman and Wermers (1995), a net flow by an investor-type that is correlated with past returns can be considered feedback trading.
The paper is organized as follows. The next section describes the variables and the data. Section 3 presents methodology and section 4 discusses empirical results for the return/fund flows tests. Concluding remarks are offered in Section 5.

2. Previous Research on Security Returns and Mutual Fund Flows

The empirical studies on the relationship between security returns and mutual fund flows at the aggregate level can be broadly divided into two groups. The first group of studies supports the assumption that equity fund flows drive market returns while the second group finds evidence that security returns affect equity fund flows. Among the studies that belong to the first group, Warther (1995) investigates the relationships between the security returns and aggregate mutual fund cash flows. His results support the popular belief that fund inflows and returns are positively related. Remolona, Kleiman, and Gruenstein (1997) examine the effects of returns on fund flows and find that net flows into the various mutual fund groups are highly correlated with market performance. Edelen and Warner (2001), and Goetzmann and Massa (2003) find that short-term fluctuation in aggregate investor demand for stocks are correlated to contemporaneous price changes and thus may move security prices. Boyer and Zheng (2004) find that the quarterly contemporaneous relations between mutual fund flows and returns are positive and significant. Their finding suggests that mutual fund sectors may exert price pressure on the market through their demand for stocks.

The second group of studies, however, finds little support for the assumption that flows drive performance. Fortune (1998) finds evidence that security returns affect future fund flows, and some fund flows affect future security returns. Potter and Schneeweis (1998) report evidence that security returns are useful in predicting flows
into aggressive growth funds and growth funds. They reject the hypothesis that equity fund flows lead security returns. Edwards and Zhang (1998) report that flows into stock and bond funds have not affected either stock or bond returns. In contrast, the magnitude of flows into both stock and bond funds are affected significantly by stock and bond returns. Fant (1999) provides evidence of feedback from returns to exchanges-out, as well as instantaneous feedback (of unknown direction) in a given month between returns and exchanges-in and -out.\(^9\) Cha and Lee (2001) contradict Edelen and Warner (2001) with regards to positive feedback. Their study cannot detect the price pressure effect, or the ability of fund flows to move stock prices. Cha and Kim (2006) employ a single equation method including error correction model and the Granger causality test for the interactions between stock prices and aggregate mutual fund flows. They find that stock returns lead stock fund flows in the U.S. financial market.

Some recent papers argue that investor sentiments are important factors in overall market movements. Goetzmann, Massa and Rouwenhorst (2000) find evidence that is consistent with existence of a pervasive investor sentiment variable. Goetzmann and Massa (2003) extract behavioral factors from individual investors’ flows in S&P 500 index mutual fund and test their incremental explanatory power using a classic asset-pricing model. Indro (2004) finds that behavior of equity fund investors is influenced not only by economic fundamentals, but also by investor sentiment. Frazzini and Lamont (2005) use mutual fund flows as a measure for individual investor sentiment for different stocks, finding that high sentiment predicts low future returns at long horizons. Braverman, Kandel, and Wohl (2005) find the negative relationship between mutual fund

\(^9\) These findings indicate that mutual fund investors use new sales/redemptions differently from exchanges, while results in the components reflect different information.
flows and the subsequent returns.  

The results of the previous studies are mixed. In contrast to previous studies that primarily examine only the relation between stock returns and equity fund flows, this paper investigates the short and long-run dynamic relations between security returns (stocks, bonds and money markets) and the corresponding mutual fund flows using longer and more comprehensive data sets in the US market.

3. Methodology

This paper studies long run and short run relations between security returns and aggregate mutual fund flows. More specifically, as we mentioned, when markets have a close relationship with one another, a seemingly unrelated regression methodology is presented to account for cross equation correlations among markets. Our main methodology in this study is a SURECM. Since the ECM is based on the notion of cointegration and the concept of causality in the Granger sense, we describe the cointegration and causality tests first. To test long-run relationships and estimate cointegrating vectors between the security prices and equity mutual fund flows, we employ Park’s (1992) CCR.  

Consider a cointegrated system where $y_t$ and $X_t$ are difference stationary, and $\varepsilon_t$ and $\nu_t$ are stationary with zero mean. Here, $y_t$ is a scalar and $X_t$ is a $(n-1) \times 1$ random vector. Let

$$y_t = X_t' \gamma + \varepsilon_t$$  \hspace{1cm} (1)

$$\Delta X_t = \nu_t$$  \hspace{1cm} (2)

---

10 Braverman, et al.(2005) find the negative relationship that causes mutual fund investors to realize a lower long-term accumulated return than long-term accumulated return on a ‘buy and hold’ position in these funds. They explain the ‘bad’ performance of mutual fund investors due to either ‘behavioral explanations’ such as investor sentiment or ‘rational market explanations’ that are based on time-varying risk premiums.

11 For unit root tests, we employed ADF and KPSS tests. See Appendix for details.
Define $\Phi(t) = E(w_t w_{t-1}')$, $\Sigma = \Phi(0)$, $\Gamma = \sum_{i=0}^{\infty} \Phi(i)$, and $\Omega = \sum_{i=-\infty}^{\infty} \Phi(i)$. Here $\Omega$ is the long run covariance matrix of $w_t$. Partition $\Omega$ as

$$
\Omega = \begin{bmatrix}
\Omega_{11} & \Omega_{12} \\
\Omega_{21} & \Omega_{22}
\end{bmatrix}
$$

and partition $\Gamma$ conformably. Define $\Omega_{11,2} = \Omega_{11} - \Omega_{12} \Omega_{22}^{-1} \Omega_{21}$ and $\Gamma_2 = (\Gamma_{12}', \Gamma_{22}')$.

The CCR procedure assumes that $\Omega_{22}$ is positive definite, implying that $X_t$ is not itself cointegrated. This assumption ensures that $(1, -\gamma)$ is the unique cointegrating vector. The OLS estimator in equation (1) is super-consistent because the estimator converges to $\gamma$ at the rate of $T$ (sample size) even when $\Delta v(t)$ and $u(t)$ are correlated. However, the OLS estimator is not asymptotically efficient in this case. To obtain an asymptotically efficient OLS estimator, Park suggests a transformed model:

$$
y_t^* = y_t + \Pi_y w_t
$$

$$
X_t^* = X_t + \Pi_x w_t
$$

Because $w_t$ is stationary, $y_t^*$ and $X_t^*$ are cointegrated with the same cointegrating vector $(1, -\gamma)$ as $y_t$ and $X_t$ for any $\Pi_y$ and $\Pi_x$. The idea of CCR is to choose $\Pi_y$ and $\Pi_x$, so that the OLS estimator is asymptotically efficient when $y_t^*$ is regressed on $X_t^*$. This requires

$$
\Pi_y^* = \Sigma^{-1} \Gamma_2 y + (0, \Omega_{12} \Omega_{22}^{-1} y')',
$$

where $\Pi_y = \Sigma^{-1} \Gamma_2$. In practice, the long-run covariance parameters in these formulas are estimated, and the estimated $\Pi_y$ and $\Pi_x$ are used to transform $y_t$ and $X_t$. As long as these parameters are estimated consistently, the CCR estimator is asymptotically efficient.
The CCR estimators have asymptotic distributions that can be essentially considered as normal distributions, implying that their standard errors have the usual interpretation. The $H(p,q)$ tests basically apply Park's $G(p,q)$ tests to CCR residuals for the null of stationarity to OLS regressions (see Park 1990 for more explanation). The $H(p,q)$ statistic converges in distribution to a $\chi^2_{p-q}$ random variable under the null hypothesis of cointegration. In particular, the $H(0,1)$ statistic tests the deterministic cointegrating restriction and the $H(1,q)$ statistic tests stochastic cointegration. One reason for using CCR is that Monte Carlo simulations in Park and Ogaki (1991) have shown that the CCR estimators have better small sample properties in terms of mean squared error than Johansen's (1988) Maximum Likelihood (ML) estimators when the sample size is small and even when the Gaussian VAR structure assumed by Johansen is true. Kahn and Ogaki (1992) find that Park's tests for the null of cointegration have reasonable small sample properties.

Based on the Granger representation theorem (Engle and Granger), we consider an ECM under the assumption that $z_t = y_t - \beta x_t$ from Equation (1) is stationary:

$$\Delta y_{it} = \mu_{0i} + \lambda_{0i} \hat{z}_{i,t-1} + \sum_{j=1}^{k} \gamma_{1,ij} \Delta x_{it-j} + \sum_{j=1}^{k} \gamma_{2,ij} \Delta y_{it-j} + u_{1,it}$$

$$\Delta x_{it} = \mu_{xi} + \lambda_{xi} \hat{z}_{i,t-1} + \sum_{j=1}^{k} \phi_{1,ij} \Delta x_{it-j} + \sum_{j=1}^{k} \phi_{2,ij} \Delta y_{it-j} + u_{2,it}$$

Equations (8) and (9) imply that security returns and fund flows are cointegrated with the cointegrating vector $(1, -\beta)$. This two equation system assumes that the long-run relationship between the two variables should be unique, but the short-run relationship between the two markets may vary according to government policies, regulations, transaction costs, and the like.
The point estimates of $\lambda$ have important economic contents. First, the stationarity of $\hat{z}_t$ requires $\lambda_{0i} \leq 0$ and $\lambda_{1i} \geq 0$. Second, the weak exogeneity of $x_t$ with respect to the long run parameters requires $\lambda_{1i} = 0$, so the deviation from the long run equilibrium, $\hat{z}_t$, does not affect $x_t$. Third, the point estimates of $\lambda_{0i}$ measure the speed of adjustment to the long run equilibrium.\(^{12}\) The larger absolute values of $\lambda_{0i}$, the faster the convergence of the deviation toward the long-run equilibrium.

SUR is applied to Equations (8) and (9) over $i$ ($i = 1, 2, 3$).\(^{13}\) Under the assumption that $z_t = y_t - \beta x_t$ from Equation (1) is stationary, Equations (8) and (9) have exactly the same explanatory variables. In this case there is no efficiency gain for SUR even when there is perfect correlation between $u_{1,it}$ and $u_{2,it}$. However, an efficiency gain can be obtained over cross-sectional units. As long as $\Delta y_{1t}$, $\Delta y_{2t}$, and $\Delta y_{3t}$ are highly correlated each other, efficiency gain is possible.

The Granger causality tests (1969) are basically tests of the predictability of time-series models. Granger causality means that if $X_{it}$ Granger-causes $Y_{it}$, then $X_{it}$ is a useful predictor of $Y_{it}$, given the other variables in the regression. The Granger causality test is based on the $F$-statistic testing the null hypothesis that the coefficients on all the values of one of the variables in the following equation are zero.

$$
Y_{it} = \alpha_{0i} + \sum_{j=1}^{4} \alpha_{ji} X_{it-j} + \sum_{j=1}^{4} \beta_{ji} X_{it-j} + \varepsilon_{it} \tag{10}
$$

The null hypothesis implies that the regressors have no predictive content for $Y_{it}$ beyond that contained in the other regressors, and the test of this null hypothesis is called the Granger causality test.

\(^{12}\) The $\lambda_{0i}$ measures how much $Y_t$ responds to a deviation from the long run equilibrium in the previous period and we use the half-life for this.

\(^{13}\) See Kim (2004) for details.
4. Data and Empirical Results

The Investment Company Institute (ICI) provides data on aggregate monthly mutual fund flows from January 1984 to December 2002.\(^{14}\) The data are divided into 21 categories by the investment objective of the funds. Within each group, cash flows are further broken down into total sales, redemptions, exchange sales, and exchange redemptions. Total sales and redemptions represent outside flows, while exchange sales and exchange redemptions represent flows among funds within a fund family. Our interest is in tracking the net flows of mutual fund money into different sectors of the market. Thus, we compute net flows (net sales) as total sales minus redemptions, plus exchange sales minus exchange redemptions.

Because the pre-1984 bond data is not comparable to post-1984 data, and because mutual funds played a much smaller role in the pre-1984 markets, our attention concentrates on the period beginning January 1984. The ICI defines larger fund categories as follows: Equity funds, Bond and Income funds, and Money Market funds. Monthly securities return data come from the Stocks, Bonds, Bills and Inflation Series of Ibbotson and Associates. The three rates of return (and return indexes) we use are the realized returns on the S&P 500 (large company stocks), on long-term U.S. Treasury bonds, and on 30-day U.S. Treasury bills. These returns are the actual rates of return experienced during the month, including both cash income (dividends or coupons) and capital value changes. To measure market returns, we select market price indexes to gauge the performance of the markets in which the funds in each larger category invest.

\(^{14}\) As shown in Mark (1995), it is likely that we have more favorable results in terms of cointegration between stock prices and equity mutual fund flows in the U.S. at the longer horizon rather than at the shorter horizon data. Low frequency monthly data on fund flows has the benefit of allowing the exploration of dynamics over longer horizon.
To gain more insight into the relationship between mutual fund flows and security market returns, we employ various tests and further examine the relationship. For a possible comovement (or contemporaneous relationship) between security market returns and mutual fund flows, we present figures 1, 2 and 3 as well as unit root tests. These figures exhibit contemporaneous relations and positive relationships over time between the two variables. Table 1 shows the results of ordinary ADF test and KPSS (1992) test. According to the ADF and KPSS tests, it is likely that all security returns and net fund flows in the mutual funds are nonstationary at the 5% significant level with the exception of fund flows in bond market in which we have mixed results. Based on the ADF test, we can reject the null of unit root, while according to the KPSS test we also reject the null of stationarity at the 10% level.

Table 2 presents the estimation results of CCR. As seen from the results, the deterministic cointegrating restrictions are rejected at the 5% level of significance, but the null of stochastic cointegrating restrictions are not rejected at the 5% significant level.\(^{15}\) In addition, the CCR provide positive estimates for cointegrating regression coefficient values, \(\hat{\beta}\), which imply positive long run relationship between security returns and fund flows.

It is of our interest to see the short run dynamics of security returns and cash flows in the mutual fund market by using an ECM. The estimation results of ordinary ECM as well as SURECM are reported in Table 3. The last two columns contain the F-statistics that test for long-term and short-term relations between stock returns and cash flows. While the results are mixed, we have statistically significant \(\hat{\lambda}_0\) coefficients in

\(^{15}\) For deterministic and stochastic cointegrations, see Ogaki and Park (1998).
stock and money markets according to SURECM results, which indicates a long-term relation between security returns and cash flows in those markets. This result is interesting because it implies that if there is a deviation from long-run equilibrium, the security returns force the deviation to go toward the long-run equilibrium. This is strong evidence that cash flows for stocks in the mutual fund market are weakly exogenous and do not respond to eliminate the deviation from long-run equilibrium. Furthermore, the hypothesis of neither long-term nor short-term relation between the two variables in the stock and money market is rejected at the 5% significant level. In effect, previous changes in stock returns cause changes in cash flows in the same direction because of positive short-term effect. However, the same is not true for cash flows. Findings from the correlation matrix of residuals in Table 3 are interesting and show that there exist positive correlations between security returns in between stock and bond markets, and in between bond and money markets, while we have negative correlations between bond and money markets. This result may imply that investors tend to move their money to the securities that yield higher returns especially in between stocks and bonds. However, we have negative correlations between fund flows in all markets except in between bond and money markets.

We also test a contemporaneous causality relation between security returns and cash flows in the mutual fund market. The null hypothesis is that security returns (cash flows) do not contemporaneously lead cash flows (security returns) in the market. According to the Granger Causality tests presented in Table (4), we reject the null hypothesis in all cases, which implies security returns contemporaneously lead cash flows in the market with the exception of money market case in which a feedback
contemporaneous relation exists between money market returns and cash flows. The positive causality from security returns to cash flows indicates that changes in the current returns cause changes in the next returns, resulting in changes in the current cash flows in the mutual fund market in the same direction.

The findings indicate that the bivariate causal relation is from market returns to equity fund flows, but not vice versa. One possibility is that Granger-causality analysis may fail to find stronger causal relationships (from flows to returns) because the appropriate time interval over which to investigate causality may be shorter than a month. If investors respond more quickly to mutual fund flows and asset returns, it may not be possible to observe Granger-causality using monthly data. It is interesting, however, that we find evidence of Granger-causality using monthly data (from returns to fund flows).

5. Conclusion

In this paper, we investigate the short-run and long-run dynamic relationships between security returns and equity mutual fund flows at the macro level in the US financial market. To find the interactions between securities returns and mutual fund flows, a couple of asset classes, bond and money markets, are also examined in the system method. The empirical evidence from CCR and SURECM indicates that there seems to be positive long-run relationship between security returns and equity mutual fund flows. We have positive correlations between security returns except the negative correlation between bond and money markets, while there exist negative correlations

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16 Brennan, in his comment on Warther (1998), suggests that lags exist between price movements and subsequent flows because not all investors are able to stay attuned to and trade on the latest news. Fund flows, in reacting to price movements, may be delayed by several days.
between mutual fund flows in stock and bond markets as well as stock and money markets. This result shows that investors tend to move their money to the securities that yield higher returns. Our empirical results from the SURECM show that equity mutual fund flows in the stock, bond and money markets are weakly exogenous and imply that if there is a deviation from long-run equilibrium, the security returns force the deviation to go toward the long-run equilibrium. This result is interesting because it shows that the fund flows do not respond to eliminate the deviation in the security markets.

Even though there is no standard way to interpret the empirical results, our findings based on dynamic relations between security returns and equity mutual fund flows as well as the causality from security returns to fund flows can be explained in several ways. Previous changes in securities returns in stock and money markets cause changes in equity fund flows in the same direction because of positive short-term effect. However, the same is not true for fund flows with the exception of money market. According to the results from the Granger causality tests, there exists a causal relation from market returns to stock investment flows especially in stock and bond markets, but not vice versa. This result indicates that security returns contemporaneously lead cash flows in the market with the exception of money market case in which a feedback contemporaneous relation exists between money market returns and cash flows. The positive causality from security returns to cash flows shows that changes in the current returns cause changes in the next returns, resulting in changes in the current cash flows in the investment trust market in the same direction. However, the Granger-causality analysis fails to find causal relationships from flows to returns.

Our empirical evidence from the system method implies that at the macro level,
there is some evidence that investors move into the stock markets in response to recent returns at monthly frequency. Investors are likely to react to fund performance and to look at the recent performance of the stock market when deciding whether to put their money into the stock market. This type of behavior seems to be rational for those who try to maximize the individual returns; in addition, this investment strategy disciplines fund managers and aligns their interests with those of investors as well. If investors respond more quickly to equity mutual fund flows and security returns, it may not be possible to observe Granger-causality with monthly data. It is interesting, however, that we find evidence of Granger-causality using monthly data (from returns to fund flows), which suggests that a longer horizon data than a daily or a weekly interval may also contain information regarding a causal relationship between security returns and equity mutual fund flows. Our empirical findings are not likely to support the popular notion of equity mutual fund flows as a driving force behind rallies in security markets. However, according to the empirical findings in this paper, the most important element explaining equity mutual fund flows seems to be security performance in the US market.
Technical Appendix

To examine dynamic relationship between security prices and aggregate mutual fund flows, we employ two types of unit root tests. They are the ADF and KPSS tests.

The standard test for unit root nonstationarity is ADF (1979) test and it is based on the following regression:

\[ \Delta X_t = \theta + (\rho - 1)X_{t-1} + \sum_{i=1}^{p} \beta_i \Delta X_{t-i} + u_t \]  \hspace{1cm} (A1)

and the null hypothesis is \((\rho - 1) = 0\), i.e. \(x_t\) possesses a unit root.

One issue in computing the ADF test is the choice of the maximum lag in the equation (A1). An insufficiently small number of lags will result in a test of incorrect size, but too large choice of lags results in a test of lower power. The method used here to decide the maximum lag is the one suggested by Hall’s general-to-specific method recommended by Campbell and Perron (1991).\(^{17}\)

The KPSS test (1992) is the test of the null hypothesis of mean stationarity in order to determine whether variables are stationary or intergrated. The KPSS test is based on the statistic:

\[ \eta(u) = \frac{T^{-2} \sum_{i=1}^{T} S_i^2}{\sigma_i^2} \text{ where } S_i = \sum_{t=1}^{T} v_t, t = 1, \ldots, T \]  \hspace{1cm} (A2)

with \(v_i\) being a residual, \(\sigma^2\) is a consistent long-run variance estimate of \(x_t\), and \(T\) represents the sample size. Kwiatkowski et al. (1992) show that the statistic \(\eta(u)\) has a non-standard distribution and critical values have been provided therein. If the calculated value of \(\eta(u)\) is large, the null of stationarity for the KPSS test is rejected.

\(^{17}\) Starting with a reasonably large value of \(p\) (24) and decrease it until the coefficient on the last included lag is significant.
References


Figure 1. S&P 500 Index and Stock Mutual Fund Flows

Figure 2. Bond Index and Bond Fund Flows
Figure 3. CD Yields and Money Market Fund Flows
Table 1. Unit Root Tests for Security Returns and Net Fund Flows

<table>
<thead>
<tr>
<th></th>
<th>ADF Test</th>
<th>KPSS Test</th>
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<tr>
<td></td>
<td>$t_{p&lt;1}$</td>
<td>$t_{p&lt;1}$</td>
</tr>
<tr>
<td>ln(SPI)</td>
<td>-2.1638</td>
<td>4.5190**</td>
</tr>
<tr>
<td>ln(LBI)</td>
<td>-1.3342</td>
<td>4.5457**</td>
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<tr>
<td>ln(TBI)</td>
<td>-1.5021</td>
<td>4.5975**</td>
</tr>
<tr>
<td>SCF</td>
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<td>1.5534**</td>
</tr>
<tr>
<td>BCF</td>
<td>-2.7652*</td>
<td>0.3930*</td>
</tr>
<tr>
<td>MCF</td>
<td>-2.2704</td>
<td>1.1607**</td>
</tr>
</tbody>
</table>

** and * represent denote significance at the 5% and 10% levels, respectively. The Critical values for $t$-statistic with 100 observations are -2.89 and -2.58 for 5% and 10% significant levels, respectively. For KPSS tests, the critical values are 0.463, and 0.347 for 5%, and 10 % levels of significance, respectively. SPI: S&P 500 Index. LBI: Long-term Treasury Bond Index. TBI: 30-day Treasury Bill index. SCF: Stock mutual fund net cash flow. BCF: Bond mutual fund net cash flow. MCF: Money market mutual fund net cash flow.

Table 2. CCR Results

$Y_t = \alpha + \beta X_t + \epsilon_t$ for CCR

<table>
<thead>
<tr>
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<th>CCR</th>
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<td>Dep. Var.</td>
<td>Ind. Var.</td>
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<tr>
<td>ln(SPI)</td>
<td>SCF</td>
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<td>ln(LBI)</td>
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<tr>
<td>Ln(TBI)</td>
<td>MCF</td>
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</table>

Note: For columns (a): numbers in parenthesis are standard errors. For columns (b): numbers in parenthesis are $p$-values. The $H(0,1)$ statistic tests the deterministic cointegrating restriction and the $H(1,q)$ statistic tests stochastic cointegration. SPI: S&P 500 Index. LBI: Long-term Treasury Bond Index. TBI: 30-day Treasury Bill index. SCF: Stock mutual fund net cash flow. BCF: Bond mutual fund net cash flow. MCF: Money market mutual fund net cash flow.
Table 3. Ordinary ECM and SURECM Results

\[ \Delta Y_t = \mu_{0i} + \lambda_{0i} \hat{Z}_{t-1} + \sum_{j=1}^{k} \gamma_{1j} \Delta X_{t-j} + \sum_{j=1}^{k} \gamma_{2j} \Delta Y_{t-j} + u_{1t} \]

\[ \Delta X_t = \mu_{ti} + \lambda_{ti} \hat{Z}_{t-1} + \sum_{j=1}^{k} \phi_{1j} \Delta X_{t-j} + \sum_{j=1}^{k} \phi_{2j} \Delta Y_{t-j} + u_{2t} \]

<table>
<thead>
<tr>
<th>Dep. Var.</th>
<th>( \hat{\lambda}_0^{(a)} )</th>
<th>( \hat{\lambda}_0^{(a)} )</th>
<th>Long-term Effect(^{(b)})</th>
<th>Short-term Effect(^{(b)})</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(SPI)</td>
<td>-0.019**</td>
<td>-0.011**</td>
<td>4.591**</td>
<td>3.477*</td>
</tr>
<tr>
<td></td>
<td>(0.0092)</td>
<td>(0.0055)</td>
<td>(0.0323)</td>
<td>(0.0616)</td>
</tr>
<tr>
<td>ln(LBI)</td>
<td>-0.008**</td>
<td>-0.005</td>
<td>1.805</td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td>(0.0037)</td>
<td>(0.0035)</td>
<td>(0.182)</td>
<td>(0.843)</td>
</tr>
<tr>
<td>ln(TBI)</td>
<td>-0.0007**</td>
<td>-0.0003*</td>
<td>2.912*</td>
<td>11.987**</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.00016)</td>
<td>(0.0868)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>SCF</td>
<td>1178.89</td>
<td>-434.82</td>
<td>0.211</td>
<td>0.477</td>
</tr>
<tr>
<td></td>
<td>(1787.98)</td>
<td>(946.96)</td>
<td>(0.646)</td>
<td>(0.482)</td>
</tr>
<tr>
<td>BCF</td>
<td>-244.09</td>
<td>213.24</td>
<td>0.245</td>
<td>5.216**</td>
</tr>
<tr>
<td></td>
<td>(507.88)</td>
<td>(430.62)</td>
<td>(0.620)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>MCF</td>
<td>29440.87</td>
<td>9126.12</td>
<td>2.325</td>
<td>7.595**</td>
</tr>
<tr>
<td></td>
<td>(9582.55)</td>
<td>(5985.35)</td>
<td>(0.127)</td>
<td>(0.005)</td>
</tr>
</tbody>
</table>

Correlation Matrix of Residual

<table>
<thead>
<tr>
<th></th>
<th>ln(SPI)</th>
<th>ln(LBI)</th>
<th>ln(TBI)</th>
<th>SCF</th>
<th>BCF</th>
<th>MCF</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(SPI)</td>
<td>1</td>
<td>0.1509</td>
<td>-0.0674</td>
<td>SCF</td>
<td>-0.0951</td>
<td>0.211</td>
</tr>
<tr>
<td>ln(LBI)</td>
<td>0.1509</td>
<td>1</td>
<td>0.0931</td>
<td>BCF</td>
<td>0.211</td>
<td>0.477</td>
</tr>
<tr>
<td>ln(TBI)</td>
<td>-0.0674</td>
<td>0.0931</td>
<td>1</td>
<td>MCF</td>
<td>0.211</td>
<td>0.477</td>
</tr>
<tr>
<td>SCF</td>
<td>SCF</td>
<td>1</td>
<td>0.211</td>
<td>0.477</td>
<td>0.1447</td>
<td>0.1110</td>
</tr>
<tr>
<td>BCF</td>
<td>BCF</td>
<td>0.211</td>
<td>0.477</td>
<td>0.1447</td>
<td>0.1110</td>
<td>1</td>
</tr>
<tr>
<td>MCF</td>
<td>MCF</td>
<td>0.211</td>
<td>0.477</td>
<td>0.1447</td>
<td>0.1110</td>
<td>1</td>
</tr>
</tbody>
</table>

* and ** denote significance at the 10% and 5% levels, respectively. For columns (a), numbers in parenthesis are standard errors. For columns (b), numbers in parenthesis are p-values. SPI: S&P 500 Index. LBI: Long-term Treasury Bond Index. TBI: 30-day Treasury Bill index. SCF: Stock mutual fund net cash flow. BCF: Bond mutual fund net cash flow. MCF: Money market mutual fund net cash flow.

Table 4. Granger Causality Test

\[ \Delta Y_t = \alpha + \sum_{i=1}^{k} \gamma_i \Delta X_{t-i} + \sum_{j=1}^{l} \lambda_j \Delta Y_{t-j} + \varepsilon_t \]

<table>
<thead>
<tr>
<th>Dep. Var.</th>
<th>Ind. Var.</th>
<th>F-Statistic</th>
<th>p-value</th>
<th>( X_{t \rightarrow G.C.} Y_t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(SPI)</td>
<td>SCF</td>
<td>0.3259</td>
<td>0.5687</td>
<td>NO</td>
</tr>
<tr>
<td>SCF</td>
<td>ln(SPI)</td>
<td>9.8394</td>
<td>0.0019</td>
<td>YES</td>
</tr>
<tr>
<td>ln(LBI)</td>
<td>BCF</td>
<td>0.0890</td>
<td>0.9148</td>
<td>NO</td>
</tr>
<tr>
<td>BCF</td>
<td>ln(LBI)</td>
<td>2.4061</td>
<td>0.0925</td>
<td>YES</td>
</tr>
<tr>
<td>ln(TBI)</td>
<td>MCF</td>
<td>2.3605</td>
<td>0.0075</td>
<td>YES</td>
</tr>
<tr>
<td>MCF</td>
<td>ln(TBI)</td>
<td>2.1327</td>
<td>0.0166</td>
<td>YES</td>
</tr>
</tbody>
</table>

"Yes (No)" indicates presence (absence) of causality with a p-value of equal or less than 0.05.